

Multi-objective Vision to Redesign Wireless Network Architectures



Trinity College Dublin

Coláiste na Tríonóide, Baile Átha Cliath

The University of Dublin

Arman Azizi

Electronic & Electrical Engineering Department

The University of Dublin

Trinity College

This dissertation is submitted for the degree of

Doctor of Philosophy

Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work. I confirm that the work has been completed in full compliance with relevant university policies, including the Academic Integrity policy, the Trinity Policy on Good Research Practice, and the guidance on AI and GenAI in Teaching, Learning, Assessment and Research.

I agree to deposit this thesis in the University's open access institutional repository or allow the Library to do so on my behalf, subject to Irish Copyright Legislation and Trinity College Library conditions of use and acknowledgement.

I consent to the examiner retaining a copy of the thesis beyond the examining period, should they so wish (EU GDPR May 2018).

Signed:

Arman Azizi

Arman Azizi
July 2026

Summary

Future wireless systems are expected to provide seamless, reliable, and wide-area connectivity across environments where conventional terrestrial architectures are no longer sufficient. Existing networks are largely built on two limiting assumptions that communication infrastructure remains confined to the ground, and that the wireless propagation environment is an uncontrollable medium. As connectivity demands expand across remote, obstructed, and heterogeneous scenarios, these assumptions become structural bottlenecks. This thesis argues that meeting such demands requires not incremental improvement, but a fundamental redesign of wireless network architecture through enabling technologies that expand both infrastructure placement and propagation control. Within this redesign, Non-Terrestrial Network (NTN) and Reconfigurable Intelligent Surface (RIS) emerge as two complementary architectural enablers. The former extends communication infrastructure into the non-terrestrial domain, while the latter transforms the radio environment into a programmable system component. Their integration creates a new architectural paradigm, i.e., non-terrestrial RIS, in which network geometry and signal propagation can be jointly controlled. Among the possible realizations of non-terrestrial RIS, RIS-enabled High Altitude Platform Station (HAPS), so-called HAPS-RIS, offers a particularly compelling balance of wide coverage, high probability of Line of Sight (LoS) connectivity, lower latency than satellite-based solutions, greater endurance and payload capacity than Unmanned Aerial Vehicle (UAV)-based alternatives, and more flexible deployment than terrestrial installations. Integrating such enabling technologies does not simplify wireless network design; rather, it expands the architectural design space by introducing new controllable dimensions in mobility, coverage, infrastructure hierarchy, and resource allocation. Consequently, the design problem becomes inherently multi-objective, since these dimensions generate competing objectives that cannot be captured through conventional single-objective formulations. On this basis, the thesis proposes a multi-objective vision for redesigning wireless network architectures, using HAPS-RIS as a representative architectural platform.

The multi-objective vision is developed through three main technical contributions.

(i) An aerodynamic HAPS-RIS architecture is introduced for connecting unconnected ground stations under time-varying channels. By geometrically modeling the predictable mobility of the platform, a multi-objective framework is established to jointly maximize cascaded channel gain, eliminate Doppler spread, and control delay spread, leading to a closed-form Pareto-optimal RIS phase shift design.

(ii) An aerostatic HAPS-RIS assisted UAV network architecture is proposed to address the scarcity of UAV infrastructure in remote coverage scenarios. A hierarchical bi-level framework is proposed where the leader problem maximizes the number of users covered by HAPS-RIS while the follower problem minimizes the number of UAVs, subject to Quality of Service (QoS) and feasibility constraints. The hierarchical optimization problem is solved via the proposed Dynamic Radius-based Zone Association with RIS clustering (DyRaZARC) and K-means Adaptive Dynamic UAV selection (KADUS) techniques. The results reveal that passive HAPS-RIS capability can substitute for active UAV deployment, exposing a direct trade-off between RIS resources and the number of required UAVs.

(iii) A unified joint multi-objective framework is proposed for fully integrated HAPS-RIS and UAV networks to maximize the covered users by HAPS-RIS, minimize the required number of UAVs, and minimize the total average UAV path loss, simultaneously, subject to QoS and feasibility constraints. A central technical achievement lies in transforming an intractable large-scale optimization problem into a scalable and implementable solution. The deployment of UAVs is shown to admit an equivalence to K-means clustering, which is proved via the proposed theoretical link between classical optimization and unsupervised learning. RIS phase shifts admit a practical closed-form design, and high-dimensional combinatorial association variables collapse into intuitive geometric and bandwidth-level control parameters, proved via the proposed mapping technique. Finally, the transformed optimization problem is solved via the proposed dynamic Pareto optimization framework which exposes the intrinsic priority structure of integrated aerial networks. The simulations uncover clear regime-dependent behaviors, indispensable trades-offs, benchmarking, and practical design guidelines. HAPS-RIS alone sufficed for low-rate services, whereas UAV assistance becomes progressively necessary as rate requirements increase. Remarkably, conventional architectures naturally emerges as special and degenerate cases of the unified framework, through a single bandwidth-portioning factor. Taken together, the strongest thesis-level insight is therefore that redesigning wireless network architecture via enabling technologies requires a multi-objective vision of managing trade-offs within an expanded design space.

To the brave people of Iran,
whose courage walks unarmed into the storm, who wager breath and being for the
simple, sovereign right to live in freedom, this humble work I lay in quiet tribute.

To my beloved wife,
the constant star by which my restless course was steered, whose patience outlasted
the longest nights, and whose faith spoke when mine fell silent.

And to my family,
in whose love I first found my strength, and in whose presence I remember who I am.

I dedicate this work.

Acknowledgements

I would like to express my sincere gratitude to my PhD supervisor, Dr. Arman Farhang, for his continuous support, guidance, and encouragement throughout my doctoral studies. His insight and mentorship have been instrumental in shaping both this research and my development as a researcher. I am deeply thankful to Dr. Mustafa Kishk at Maynooth University, Ireland, for his collaboration and valuable contributions. His deep knowledge and constructive discussions have played an important role in shaping the direction and quality of this work. I would also like to acknowledge Dr. Hamed Ahmadi at the University of York, UK, for his kind support in facilitating international collaboration and enabling my remote research visit. My thanks also extend to Dr. Mostafa Rahmani for his support and insightful discussions during this period.

I gratefully acknowledge the ADVANCE CRT programme, led by Prof. Dirk Pesch, for providing an outstanding research environment and continuous support throughout my PhD. The programme offered world-class opportunities, including summer schools, research colloquiums, and workshops, as well as strong encouragement and support for international research collaboration. I also thank CONNECT, led by Prof. Dan Kilper, for providing unique opportunities and support to its members. Finally, I would like to thank the Electronic and Electrical Engineering Department and the School of Engineering at Trinity College Dublin for their continuous support during my PhD journey.

Table of contents

List of figures	xv
List of tables	xix
1 Introduction	1
1.1 Thesis Contributions	4
1.1.1 Connect the Unconnected with Aerodynamic HAPS-RIS . . .	4
1.1.2 UAV-based Networks Assisted by Aerostatic HAPS-RIS . . .	5
1.1.3 HAPS-RIS and UAV Integrated Networks	5
1.2 Thesis Organization	6
1.3 Track Record	7
1.3.1 Publications	7
1.3.2 Selected Talks and Poster Presentations	7
1.3.3 Research Visit	8
2 Background and Literature Review	11
2.1 To Redesign Wireless Network Architectures	11
2.1.1 HAPS Technology	13
2.1.1.1 Aerodynamic HAPS	15
2.1.1.2 Aerostatic HAPS	17
2.1.1.3 Aerodynamic HAPS Versus Aerostatic HAPS	18
2.1.2 RIS-assisted Networks	19
2.1.3 RIS-enabled HAPS (HAPS-RIS)-assisted Networks	23
2.1.4 UAVs in the Action	26
2.1.5 Why Multi-objective Vision is Needed?	27
2.2 Multi-objective Vision	28
2.3 Lessons Learned and Conclusion	32

3	Connect the Unconnected with Aerodynamic HAPS-RIS	35
3.1	The Main Contributions of this Chapter	35
3.2	The Proposed Network	37
3.3	Proposed Multi-objective Optimization Problem	41
3.4	Proposed RIS Phase Shift Design:	
	Pareto Optimal Solution	41
3.5	Numerical Evaluations of The Proposed RIS Phase Shift Design . . .	45
3.6	Lessons Learned and Conclusion	49
4	Exploring the Impact of Aerostatic HAPS-RIS on UAV-based Networks:	
	A Hierarchical Framework	53
4.1	The Main Contributions of this Chapter	54
4.2	Proposed Network Architecture	55
4.3	Problem Formulation and Proposed Solution Techniques	57
	4.3.1 Proposed HAPS-RIS Zone Design	57
	4.3.2 Proposed UAV Zone Design	61
	4.3.3 Model Limitations	63
4.4	Numerical Evaluations	63
	4.4.1 Performance Evaluation of the Standalone HAPS-RIS Architecture	65
	4.4.2 Performance Evaluation of the Integrated HAPS-RIS and UAV	
	Architecture	66
4.5	Lessons Learned and Conclusion	68
5	HAPS-RIS and UAV Integrated Networks: A Unified Joint Multi-objective Framework	71
5.1	The Main Contributions of this Chapter	72
	5.1.1 A Comprehensive Unified System-level Framework	72
	5.1.2 A Low-Complexity Solution Strategy	73
	5.1.3 System-Level Insights and Design Guidelines	73
5.2	The Proposed Network Architecture	74
	5.2.1 UAV-based Network Architecture	75
	5.2.2 HAPS-RIS assisted Network Architecture	76
5.3	The Proposed Multi-objective Joint Optimization Problem	77
5.4	The Proposed Solution Method	80
	5.4.1 Proposed Upper Bound and k -Means Equivalence	81

5.4.2	Proposed Practical RIS Phase Shift Design	82
5.4.3	Proposed Mapping Technique	83
5.4.4	Proposed Dynamic Pareto Optimization Framework	86
5.5	Complexity and Convergence Analysis	89
5.5.1	Computational Complexity	89
5.5.2	Convergence Analysis	90
5.6	Case Study and Numerical Analysis	91
5.6.1	UAV-free Case Study: A Degenerate Case of OP 4	93
5.6.2	UAV in Action but Separate Spectrum Case Study: A Disjoint Degenerate Case of OP 4	95
5.6.3	UAV in Action with Shared Spectrum: Unified Joint Case Study and Comparison with its Baselines	98
5.7	Lessons Learned and Conclusion	102
6	Conclusions and Future Works	105
6.1	The Core Insights of My Thesis	105
6.1.1	From Mobility to Controllability	105
6.1.2	From Scarcity to Coordination	106
6.1.3	From Coordination to Coupling	107
6.2	The Lessons Learned	108
6.3	Limitations	109
6.4	Future Research Directions	109
6.4.1	Integrated Sensing and Communication (ISAC)	109
6.4.2	Space-Air-Ground Integrated Networks (SAGIN)	110
6.4.3	Physical layer security	110
6.4.4	Self-Evolving Network Architectures	111
6.4.5	Digital Twin Technology	111
6.4.6	Architecture as a Continuous Field	112
6.4.7	Towards Practical Deployment	112
6.5	Closing Remarks	112
	References	115

List of figures

2.1	The Proposed 6G Roadmap	12
2.2	The main types of non-terrestrial Infrastructures.	13
2.3	Integration of non-terrestrial and terrestrial infrastructures.	13
2.4	Study of environmental parameters in the stratosphere layer [40]. . .	14
2.5	Classification of well-known HAPS projects.	16
2.6	The geometry of connecting the transmitter and receiver via RIS through blockage.	20
2.7	Motivations and contributions of this chapter at a glance.	22
2.8	Heterogeneous infrastructures: Aerostatic HAPS-RIS and UAVs. . . .	26
3.1	Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.	36
3.2	Proposed network architecture based on aerodynamic HAPS-RIS. . .	38
3.3	Geometrical mobility pattern of RIS elements based on the predictable mobility of the aerodynamic HAPS.	38
3.4	The proposed Pareto Optimal Solution Method	42
3.5	Cascade channel gain versus RIS dimensions at $t = t_0$	46
3.6	Delay spread upper bound versus RIS dimensions at $t = t_0$	47
3.7	Cascade channel gain versus time for different RIS dimensions. . . .	48
3.8	Delay spread upper bound versus time for different RIS dimensions. .	49
4.1	Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.	54
4.2	The Proposed Network Architecture	56

4.3	Percentage of covered users by HAPS-RIS versus number of RIS element for the rate requirements 64, 128, and 256 kbps when the CS transmit power is 40 dBm and only HAPS-RIS setup is in use.	64
4.4	Percentage of covered users by HAPS-RIS versus CS Transmit power for the rate requirements 64, 128, and 256 kbps when the number of RIS elements are 3.5×10^5 and only HAPS-RIS setup is in use.	65
4.5	Required number of total RIS elements in logarithmic scale versus logarithm of the minimum rate requirements to provide full coverage, where only HAPS-RIS setup is in use.	67
4.6	Trade-off between the number of UAVs and RIS elements to provide the full coverage. This is achieved by exploiting the proposed DyRaZARC and KADUS techniques where both HAPS-RIS setup and UAVs are in use.	67
5.1	Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.	72
5.2	The Proposed System Model	75
5.3	The proposed geometric model of OP 4	87
5.4	The proposed dynamic Pareto optimization method to solve OP 4	89
5.5	Percentage of covered users by HAPS-RIS versus number of RIS elements in the high-rate regime for the UAV-free case with the CS transmit power of 40 dBm.	93
5.6	Percentage of covered users by HAPS-RIS versus number of RIS elements in the low-rate regime for the UAV-free case with the CS transmit power of 40 dBm.	94
5.7	Percentage of covered users by HAPS-RIS versus CS transmit power in the high-rate regime with 10^7 RIS elements for the UAV-free case.	94
5.8	Percentage of covered users by HAPS-RIS versus CS transmit power in the low-rate regime with 3.5×10^5 RIS elements for the UAV-free case.	95
5.9	An example of user association illustrating the coexistence of HAPS-RIS and UAVs via zone-based association and UAV clustering.	96
5.10	Minimum Required number of total RIS elements versus the wide range of rate requirements to provide full coverage.	97
5.11	Trade-off between the minimum required number of UAVs and the number of RIS elements to provide full coverage in the high-rate regime.	97

5.12	Trade-off between the minimum required number of UAVs and the number of RIS elements to provide full coverage in the low-rate regime.	98
5.13	Percentage of covered users by HAPS-RIS versus bandwidth portioning factor in the high-rate regime, where 10^7 RIS elements are exploited.	99
5.14	Percentage of covered users by HAPS-RIS versus bandwidth portioning factor in the low-rate regime, where 3.5×10^5 RIS elements are exploited.	100
5.15	Minimum required number of UAVs versus bandwidth portioning factor in the high-rate regime with 10^7 RIS elements.	101
5.16	Minimum required number of UAVs versus bandwidth portioning factor in the low-rate regime with 3.5×10^5 RIS elements.	101

List of tables

2.1	The Aerodynamic HAPS projects.	17
2.2	The Aerostatic HAPS projects.	18
2.3	Taxonomy of HAPS-RIS assisted networks.	24

List of Acronyms

NTN Non-Terrestrial Network

LEO Low Earth Orbit

MEO Medium Earth Orbit

GEO Geostationary Earth Orbit

HAPS High Altitude Platform Station

LAPS Low Altitude Platform Station

SHARP Stationary High Altitude Relay Platform

CRC Communication Research Center

NASA National Aeronautics and Space Administration

ERAST Environmental Research Aircraft and Sensor Technology

BAE British Aerospace

PHASA Persistent High Altitude Solar Aircraft

JAXA JAPAN Aerospace Exploration Agency

CAPANINA Communications from Aerial Platform Networks Delivering Broadband
Communications for All

RIS Reconfigurable Intelligent Surface

Satellite-RIS RIS-enabled Satellite

UAV-RIS RIS-enabled UAV

HAPS-RIS RIS-enabled HAPS

CS Control Station

UAV Unmanned Aerial Vehicle

QoS Quality of Service

LoS Line of Sight

NLoS Non-Line of Sight

5G Fifth-generation Mobile Network

6G Sixth-generation Wireless Network

SAGIN Space-Air-Ground Integrated Networks

ISAC Integrated Sensing and Communication

DyRaZARC Dynamic Radius-based Zone Association with RIS clustering

KADUS K-means Adaptive Dynamic UAV selection

Chapter 1

Introduction

Wireless network design is undergoing a fundamental transformation due to the fact that the architectural assumptions that have guided previous generations are reaching their limits. Traditional wireless systems are built upon a simple premise that the communication infrastructure is deployed on the ground, and the wireless environment is treated as an uncontrollable medium through which signals propagate. This separation between infrastructure and environment has shaped decades of design methodologies, where performance improvements are achieved through densification, spectrum expansion, and signal processing enhancements. However, this paradigm becomes increasingly fragile as networks scale in both spatial extent and service diversity [1–3]. The assumption that coverage can be achieved through terrestrial infrastructure alone fails when connectivity must extend seamlessly across various areas. The assumption that the propagation environment is fixed and uncontrollable becomes a bottleneck where blockage and sensitivity to geometry dominate system performance. These limitations are structural and indicate that the network architecture needs to be redesigned [2, 4, 5]. The emerging vision of Sixth-generation Wireless Network (6G) cannot be interpreted as a continuation of terrestrial network evolution. Instead, it demands a reconfiguration of the network into a three-dimensional, multi-layered architecture where communication is no longer confined to the terrestrial plane [6]. In such an architecture, infrastructure is distributed across multiple layers, and the propagation environment itself becomes a controllable component of the system. This shift fundamentally alters the nature of the design problem. Rather than optimizing isolated links or individual network layers, the challenge becomes one of orchestrating interactions across spatially distributed and functionally heterogeneous components. This architectural transition is enabled by two key technological directions [6]. The

first is the introduction of NTN layers, which extend communication infrastructure into the aerial and space domains. By elevating network nodes above the ground, NTN introduces new geometric degrees of freedom, enabling wide-area coverage and increased LoS connectivity [7–15]. The second is the introduction of RIS, which transforms the wireless environment from a passive medium into an actively controllable entity. Through programmable reflection, RIS allows the propagation of electromagnetic waves to be shaped, redirected, and optimized in accordance with system objectives [16–20]. Individually, these enabling technologies address different limitations of terrestrial networks. NTN expands where signals can propagate, while RIS controls how they propagate. When combined, they give rise to a fundamentally novel architectural paradigm in which spatial deployment and propagation control are jointly designed [21].

Within the NTN hierarchy, different platforms offer distinct trade-offs in terms of coverage, latency, and operational constraints. Among these, HAPS emerges as a particularly compelling architectural element due to its position in the stratosphere, between low-altitude UAVs and satellite systems. This intermediate placement allows HAPS to combine the wide-area coverage characteristics of satellites with the lower latency and deployment flexibility of aerial platforms. Operating at high altitudes, HAPS establishes predominantly LoS communication links, which significantly enhance coverage and connectivity [22–26]. Beyond its geometric advantages, HAPS also offers substantial payload capacity, enabling the integration of advanced communication components and facilitating its role as a multi-functional network node. Its extended operational endurance further supports the realization of persistent aerial infrastructure, distinguishing it from energy-constrained UAV systems. At the same time, compared to satellite platforms, the lower altitude of HAPS results in reduced propagation delay and more flexible deployment, while still maintaining large coverage footprints. This combination of coverage, latency, persistence, and flexibility positions HAPS not merely as an additional network layer, but as a structurally significant component in the emerging multi-layer architecture. In particular, its ability to provide wide-area, quasi-stationary service makes it a promising candidate for hosting higher-level network functionalities, bridging the gap between terrestrial and space-based infrastructures [27]. Embedding RIS within HAPS leads to the concept of HAPS-RIS, where a programmable surface is installed on HAPS. The combination of high-altitude placement and programmable reflection introduces a new set of design capabilities, enabling the joint control of network geometry and propagation [21, 28]. This design introduces new forms of coupling between mobility, coverage, and resource

allocation, fundamentally reshaping the design space of wireless networks. However, the integration of these enabling technologies does not simplify the design problem. It expands the architectural design space by introducing new controllable dimensions, including platform mobility, reflective surface configuration, hierarchical coordination, and resource allocation strategies. These dimensions are tightly coupled, giving rise to complex interdependencies and trade-offs. Hence, enabling technologies do not directly solve network design challenges; instead, they enlarge the space of feasible solutions. Accordingly, a unifying theme emerges as *“Redesigning the wireless network architecture via enabling technologies requires a multi-objective vision of managing trade-offs within an expanded design space.”*

This perspective naturally leads to the formulation of the following research questions, from the lens of multi-objective vision, addressed in this thesis. The first question arises at the level of link dynamics which introduces multi-objective framework, proposing a fundamental trade-offs between channel gain and time-varying effects. The second question emerges at the level of network architecture coordination which introduces hierarchical coordination and trade-offs between passive and active infrastructures. The third question emerges at the level of network architecture coupling which introduces a unified joint multi-objective framework where the infrastructures are fully integrated.

Research Question 1

- How can wireless network architectures be redesigned through aerodynamic HAPS-RIS platforms to provide connectivity for unconnected ground stations under time-varying channels?

Research Question 2

- How can wireless network architectures be redesigned through aerostatic HAPS-RIS and UAV platforms to maximize service coverage while reducing UAV deployment requirements?

Research Question 3

- How can HAPS-RIS and UAV infrastructures be jointly designed within a unified system-level multi-objective framework?

1.1 Thesis Contributions

This thesis is structured around three main technical contributions which are not isolated solutions to independent problems, but successive steps in uncovering the structure of an expanded architectural design space. As enabling technologies, e.g., HAPS and RIS are integrated into wireless networks, the problem is no longer one of improving individual links or optimizing single layers, but of understanding how new degrees of freedom reshape the system as a whole. In this setting, mobility, infrastructure hierarchy, and resource allocation cease to be separate design dimensions; instead, they become tightly coupled components of a unified architectural problem.

1.1.1 Connect the Unconnected with Aerodynamic HAPS-RIS

The first contribution of this thesis, which is presented in Chapter 3, establishes a mobility-aware architectural framework for HAPS-RIS-enabled wireless networks, where mobility is no longer treated as an impairment but as a controllable dimension of the system. In conventional designs, the dynamics of aerial platforms introduce uncertainty in the channel and are typically mitigated through robust or adaptive techniques. In contrast, this work reinterprets mobility as a structural property that can be modeled and exploited at the architectural level. To this end, a novel HAPS-RIS-enabled network architecture is introduced, in which RIS is mounted on an aerodynamic HAPS to connect the unconnected ground stations. The key departure from existing approaches lies in the geometric modeling of the platform motion at the level of individual RIS elements. By linking the trajectory of the HAPS to the spatial configuration of the RIS, the resulting cascaded channel is characterized in terms of its time-varying geometry, revealing the fundamental interactions between channel gain, delay spread, and Doppler spread. This geometric perspective exposes a multi-objective structure in the design problem. Rather than optimizing a single performance metric, the system must balance competing objectives that arise from the mobility-induced dynamics of the channel. Accordingly, a multi-objective optimization framework is proposed, capturing these trade-offs within a unified setting. By exploiting the predictability of the aerodynamic HAPS trajectory, a closed-form Pareto-optimal solution for the RIS phase configuration is derived.

1.1.2 UAV-based Networks Assisted by Aerostatic HAPS–RIS

The second contribution of this thesis, which is presented in Chapter 4, shifts the focus from link-level design to the architectural organization of heterogeneous non-terrestrial networks. It addresses a fundamental limitation of UAV-based network, which is the limitation on the number of UAVs. Rather than scaling the number of UAVs, We introduce a supportive HAPS-RIS layer that fundamentally alters how coverage is provisioned. In the proposed novel network architecture, the service region is structurally partitioned into heterogeneous zones, each associated with a distinct infrastructure layer. Users are no longer served by a single type of node; instead, they are dynamically assigned either to a HAPS-RIS zone or a UAV zone, depending on their spatial and performance characteristics. This partitioning transforms user association into an architectural decision, where coverage, rate requirements, and resource availability jointly determine the role of each layer. This structure reveals a key insight that the capability of the passive HAPS-RIS layer can directly substitute for the need of active UAV deployment. Increasing the number of RIS elements expands the effective coverage of the HAPS-RIS zone, thereby reducing the number of users that must be served by UAVs. Accordingly, the number of required UAVs is no longer a fixed constraint, but a variable that can be controlled through the configuration of the RIS. This exposes a fundamental trade-off between passive and active infrastructure resources. To capture this interaction, a hierarchical bilevel optimization framework is proposed. The upper-level problem determines the zone boundary and configures the RIS to maximize the number of users served by the HAPS-RIS layer under rate constraints. The lower-level problem minimizes the number of UAVs required to serve the remaining users. To ensure practical tractability, the framework is complemented by geometry-informed and adaptive solution techniques, enabling efficient realization of the hierarchical design. Through this contribution, the network is no longer viewed as a collection of independent components, but as a coordinated multi-layer system in which infrastructure roles are dynamically shaped. It demonstrates that architectural design can transform resource limitations into controllable trade-offs.

1.1.3 HAPS-RIS and UAV Integrated Networks

The third contribution of this thesis, which is presented in Chapter 5, elevates the scenario from hierarchical coordination to fully integrated system design, where the network is treated as a unified architectural entity rather than a collection of interacting layers. The key design dimensions of the network architecture include UAV

deployment, user association, clustering, resource allocation, and RIS configuration which are intrinsically coupled. Any attempt to optimize them in isolation fails to capture the structure of the design space and leads to inefficient decisions. To overcome this limitation, a comprehensive system-level framework is developed in which HAPS-RIS and UAV-assisted networks are jointly designed under a unified multi-objective optimization problem to simultaneously maximize the number of covered users by HAPS-RIS, minimize the number required UAVs, and minimize the total average UAV pathloss subject to QoS and practical network constraints. In this framework, spatial, spectral, and infrastructural variables are optimized simultaneously. This design reveals that passive and active infrastructures do not operate independently, but form a unified resource pool whose interactions determine the achievable performance of the network. A central outcome of this contribution is the derivation of theoretical structures that expose hidden relationships within the high-dimensional optimization problem. In particular, it is shown that UAV deployment and user association can be interpreted through clustering principles, establishing a direct connection between classical optimization and unsupervised learning. This insight transforms a complex combinatorial problem into a structured and tractable form. In parallel, geometry-driven formulations enable practical closed-form designs for RIS configuration, significantly reducing implementation complexity. Furthermore, the rest of the combinatorial variables are transformed into zone boundary radius and the bandwidth portioning factor, and finally the transformed optimization problem is solved via the proposed dynamic Pareto optimization method. Beyond theoretical development, this unified framework enables the extraction of system-level design guidelines that characterize the behavior of the network under different operating conditions. It reveals a regime-dependent architecture, where HAPS-RIS alone can support the network under low-rate requirements, while higher rate regimes necessitate the complementary deployment of UAVs. It further quantifies a fundamental trade-off between RIS capability and UAV density, showing that increasing the scale of passive infrastructure can directly reduce the need for active aerial deployment.

1.2 Thesis Organization

Chapter 2 is the background and literature review which establishes the foundation by identifying the limitations of terrestrial networks and positioning HAPS and RIS as enabling technologies that introduce new architectural degrees of freedom. This chapter also studies the foundation of multi-objective optimization. Chapter 3 studies

the first technical contribution of the thesis where a multi-objective framework is proposed for an aerodynamic HAPS-RIS-enabled network. Chapter 4 studies the second technical contribution of the thesis where a hierarchical bi-level framework is proposed for a UAV-based network assisted by aerostatic HAPS-RIS. Chapter 5 studies the third technical contribution of the thesis where a unified joint multi-objective framework is proposed for a network supported by UAVs and aerostatic HAPS-RIS. Finally, Chapter 6 concludes the thesis, and outlines the future research direction.

1.3 Track Record

In the following, the research outputs and scholarly activities associated with this thesis are presented, reflecting both the progression of the work and its dissemination within the research community.

1.3.1 Publications

1. **A. Azizi**, A. Farhang, “RIS Meets Aerodynamic HAPS: A Multi-objective Optimization Approach,” Published in IEEE Wireless Communication Letters (WCL), 2023 [29].
2. **A. Azizi**, M. Kishk, A. Farhang. “Exploring the Impact of HAPS-RIS on UAV-based Networks: A Novel Network Architecture,” published in IEEE PIMRC, Turkey, 2025 [30].
3. **A. Azizi**, M. Rahmani, M. Kishk, H. Ahmadi, and A. Farhang, “HAPS-RIS and UAV Integrated Networks: A Unified Joint Multi-objective Framework,” Under first revision, IEEE Transactions on Vehicular Technology (TVT), 2025 [31].

1.3.2 Selected Talks and Poster Presentations

1. **A. Azizi**, A. Farhang. “Reflect From the Smart Sky: RIS-enabled Aerodynamic HAPS-assisted Networks,” Inaugural School of Engineering Research Symposium (SERS), Trinity College Dublin, Ireland, 2023, [32].
2. **A. Azizi**, M. Kishk, and A. Farhang. “Transforming the Skies: How HAPS-RIS is Shaping the Future of UAV Networks,” Second School of Engineering Research Symposium (SERS), Trinity College Dublin, Ireland, 2024 [33].

3. **A. Azizi**, M. Kishk, and A.Farhang. “What Will Be The Network Architecture For Next Generation Networks?” Research Ireland ADVANCE CRT Research Colloquium, Tralee, Ireland, 2024 [34].

1.3.3 Research Visit

1. A. Azizi, Remote Research Visit with Dr. Hamed Ahmadi’s Research Group, University of York, United Kingdom, 2025.

Chapter 2

Background and Literature Review

A central objective of sixth generation wireless networks (6G) is to provide ubiquitous and reliable connectivity, enabling seamless connectivity for users and devices anytime and anywhere, at sustainable deployment costs [1–3, 35, 36]. However, such ambitious goals cannot be fulfilled by existing wireless network architectures, which primarily rely on terrestrial infrastructures and operate over largely uncontrollable propagation environments. Therefore, as clarified in Chapter 1, achieving the vision of future wireless systems requires a fundamental redesign of wireless network architectures rather than incremental improvements to existing deployments [1–3, 35, 36]. Fig. 2.1 conceptually illustrates this transition, where the evolution of wireless generations culminates in 6G.

2.1 To Redesign Wireless Network Architectures

As elaborated in Chapter 1, to redesign wireless network architectures, it is essential to exploit high-impact enabling technologies that introduce new capabilities and degrees of freedom, allowing them to serve as fundamental building blocks of next-generation networks. Among the emerging technologies, NTN and RIS have attracted significant attention due to their strong potential to redesign wireless network architectures [21]. While NTN introduces an active non-terrestrial communication layer that expands network coverage and connectivity, RIS enables a programmable wireless environment capable of intelligently controlling signal propagation [21]. Fig. 2.2 illustrates the main types of non-terrestrial infrastructures envisioned for 6G networks, including satellite systems, HAPS, and Low Altitude Platform Station (LAPS). It highlights three main satellite orbit classes, namely Low Earth Orbit (LEO), Medium Earth

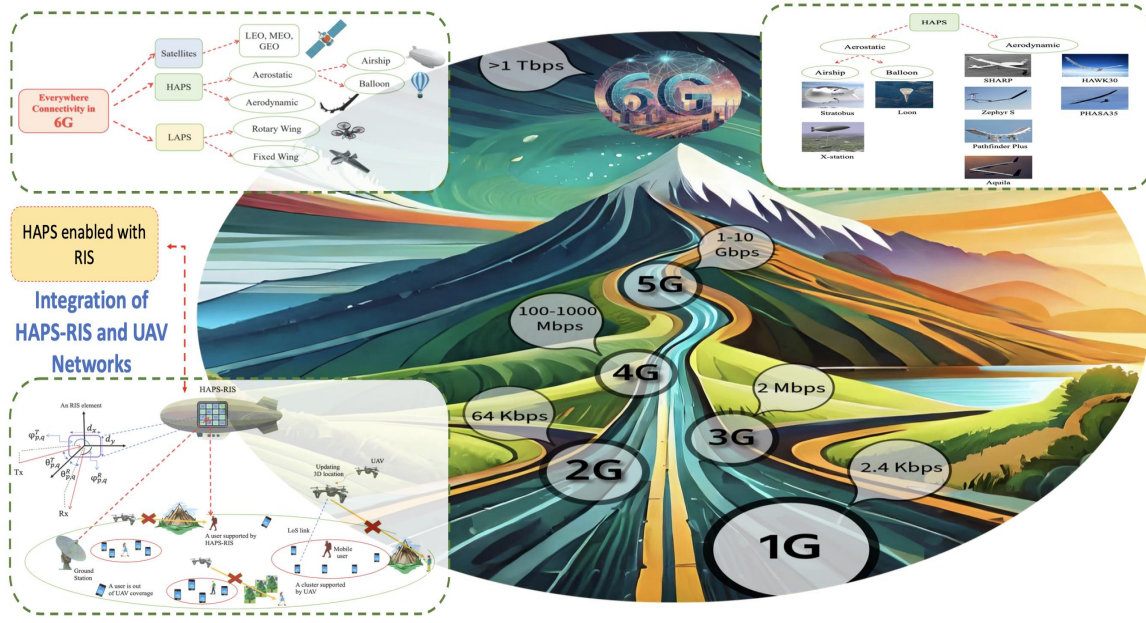


Fig. 2.1 The Proposed 6G Roadmap

Orbit (MEO), and Geostationary Earth Orbit (GEO). HAPS is categorized into two principal configurations, i.e., aerodynamic and aerostatic platforms. The former one relies on lift and propulsion to maintain flight, while the latter one, e.g., airships and balloons, exploit buoyancy to enable long-duration operation in the stratosphere [27, 37]. LAPS is typically categorized into rotary-wing UAVs and fixed-wing UAVs [11]. Fig. 2.3 illustrates the redesigned network architecture, empowered by enabling technologies, that integrates terrestrial and non-terrestrial infrastructures to enable ubiquitous connectivity.

Among the available non-terrestrial platforms, HAPS stands out as a particularly promising candidate for telecommunication infrastructure. Positioned in the stratosphere between low-altitude UAVs and satellites, HAPS occupies a strategic middle level that combines the strengths of both layers while mitigating their limitations. Operating at significantly higher altitudes than UAVs, HAPS enables predominantly line-of-sight (LoS) communication links, which translate into substantially wider coverage areas and improved connectivity [22–26]. At the same time, the larger physical size of HAPS platforms allows them to carry heavier payloads and multiple communication instruments, making them versatile nodes capable of supporting a wide range of telecommunication services. Furthermore, HAPS platforms offer considerably longer operational endurance compared to UAVs, enabling persistent aerial communication

infrastructures. In contrast to satellite systems, the lower operational altitude of HAPS results in significantly reduced propagation delay and lower deployment costs while still maintaining wide-area coverage. This unique balance between coverage, latency, endurance, and deployment flexibility positions HAPS as a powerful enabler for ubiquitous connectivity and a key building block in the redesign of future 6G wireless network architectures [24, 38, 39].

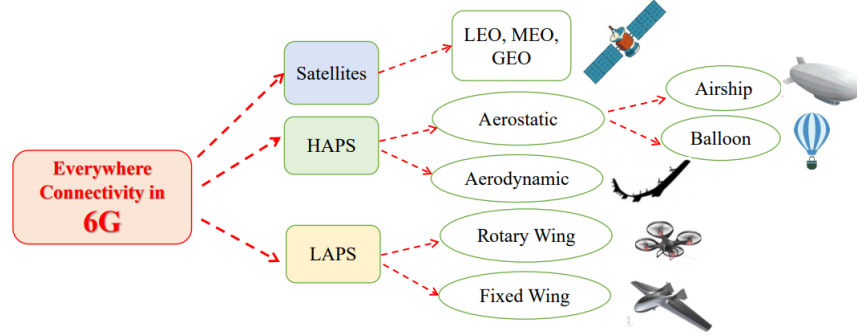


Fig. 2.2 The main types of non-terrestrial Infrastructures.

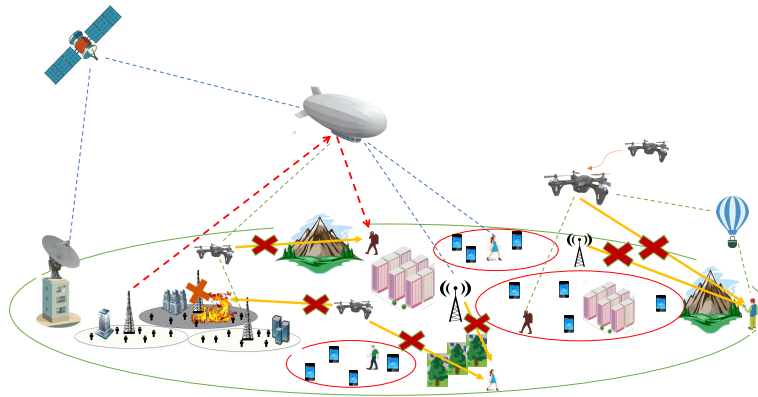


Fig. 2.3 Integration of non-terrestrial and terrestrial infrastructures.

2.1.1 HAPS Technology

HAPSs are aerial network nodes that operate in the stratosphere at altitudes of approximately 20 km, forming a unique communication layer between terrestrial and space-based infrastructures. At this altitude, a single HAPS platform can provide coverage with a radius of roughly 50 km while maintaining a quasi-stationary position

relative to the Earth [22–26]. The stratosphere offers particularly favorable operating conditions for such platforms. Weak winds reduce the energy required for stabilization, while the relatively low air density enables efficient high-altitude flight. Consequently, HAPS systems can leverage large surface areas equipped with solar panels and onboard energy storage to sustain long-duration operations, ranging from several hours to even years. The choice of the stratospheric altitude around 20 km is not arbitrary; rather, it represents a sweet spot. As can be seen in Fig. 2.4, at the altitude around 20 km, the critical environmental parameters, e.g., air density, wind speed, and temperature, simultaneously reach minimal levels, creating an ideal operational regime for persistent non-terrestrial platforms [40].

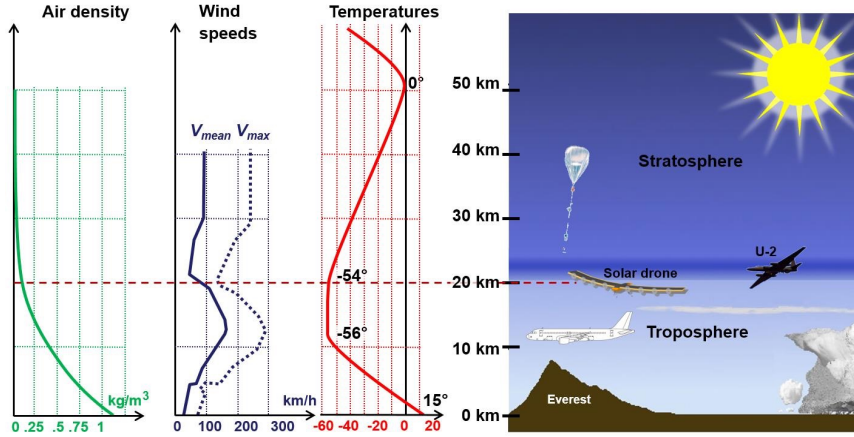


Fig. 2.4 Study of environmental parameters in the stratosphere layer [40].

A distinctive feature of HAPS is that it operates in the stratosphere, typically at altitudes on the order of 20 kilometers above the ground. At such elevations, the HAPS-to-ground propagation path is largely unobstructed and therefore dominated by a LoS component. This observation motivates the adoption of a free-space propagation model exploiting the Friis transmission law. Let the position of the HAPS be denoted by $\mathbf{r}^H = (x^H, y^H, z^H) \in \mathbb{R}^3$, and let the position of ground user i be $\mathbf{r}_i = (x_i, y_i, z_i) \in \mathbb{R}^3$. The distance between HAPS and user can be determined as

$$d_i^H = \|\mathbf{r}^H - \mathbf{r}_i\| = \sqrt{(x^H - x_i)^2 + (y^H - y_i)^2 + (z^H - z_i)^2}. \quad (2.1)$$

To further expose the propagation geometry, let the horizontal ground distance between the HAPS projection and user i be $\rho_i = \sqrt{(x^H - x_i)^2 + (y^H - y_i)^2}$, so that the elevation angle observed from the user side is $\phi_i = \tan^{-1}\left(\frac{z^H - z_i}{\rho_i}\right)$. For stratospheric

platforms, ϕ_i is typically sufficiently large over a substantial service region, which makes the LoS probability dominant. Under this LoS-dominant regime, the path loss of the HAPS link can be obtained by the Friis law as [41]

$$L_i^H = \left(\frac{4\pi d_i^H}{\lambda_c} \right)^2 = \left(\frac{4\pi f_c d_i^H}{c_0} \right)^2, \quad (2.2)$$

where f_c denotes the carrier frequency, $\lambda_c = \frac{c_0}{f_c}$ is the carrier wavelength, and c_0 is the speed of light. Equation (2.2) characterizes the large-scale attenuation of the HAPS channel. Equivalently, the associated channel power gain is $|h_i^H|^2 = (L_i^H)^{-1} = \left(\frac{\lambda_c}{4\pi d_i^H} \right)^2$. When the directional gains of the transmitting and receiving antennas are accounted for, the effective power gain becomes [28]

$$|h_i^H|^2 = G^H G_i \left(\frac{\lambda_c}{4\pi d_i^H} \right)^2, \quad (2.3)$$

where G^H and G_i denote the antenna gains of the HAPS and user i , respectively. At the complex baseband level, the LoS HAPS channel can therefore be represented as

$$h_i^H = \sqrt{G^H G_i} \frac{\lambda_c}{4\pi d_i^H} \exp\left(-j \frac{2\pi}{\lambda_c} d_i^H\right). \quad (2.4)$$

The concept of HAPS is not new and has attracted research and industrial interest for more than four decades. In the following, several practical HAPS projects are studied, highlighting their technical specifications and demonstrating their potential to serve as integral components of future wireless networks. Examining these real-world projects not only illustrates the maturity of HAPS technology but also provides practical benchmarks that can inform the simulation parameters and system models considered in this thesis, thereby bridging the gap between theoretical research and industrial deployment. Fig. 2.5 provides a conceptual snapshot of several well-known HAPS projects. Broadly, these platforms can be categorized into two principal classes, e.g., aerostatic and aerodynamic systems. While aerostatic platforms utilize buoyancy to remain airborne, aerodynamic platforms utilize dynamic forces resulting from their movement through the air to achieve lift [42].

2.1.1.1 Aerodynamic HAPS

Aerodynamic HAPS platforms represent a major technological pathway toward persistent stratospheric communication infrastructures. Early experiments such as

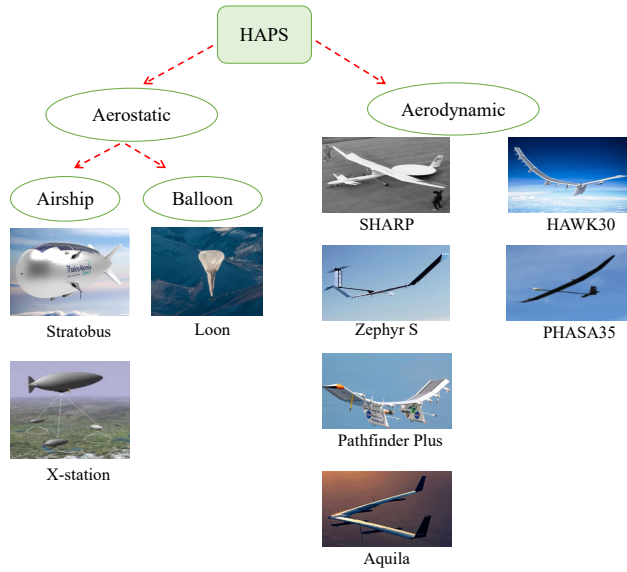


Fig. 2.5 Classification of well-known HAPS projects.

Canada's Stationary High Altitude Relay Platform (SHARP) project, conducted by Communication Research Center (CRC), demonstrated the feasibility of high-altitude communication platforms powered by microwave energy, achieving reliable telecommunications from approximately 21 km altitude [43]. Subsequent advances were driven by National Aeronautics and Space Administration (NASA), Environmental Research Aircraft and Sensor Technology (ERAST) program, which developed solar-powered platforms including Pathfinder, Centurion, and Helios, marking important milestones in long-endurance stratospheric flight and enabling early demonstrations of broadband communication services [44]. Building on these foundations, modern aerodynamic HAPS projects focus on sustained high-altitude operation and practical telecommunication deployment. Airbus' Zephyr S has achieved record-breaking endurance exceeding 25 days of continuous flight while carrying communication payloads powered entirely by solar energy [45]. Similarly, Facebook's Aquila project explored solar-powered aerial platforms aimed at delivering broadband connectivity to remote regions [46–48]. More recent developments such as HAPSMobile's HAWK30 and British Aerospace (BAE) Systems' Persistent High Altitude Solar Aircraft (PHASA)-35 further demonstrate the growing maturity of aerodynamic HAPS platforms, capable of operating at stratospheric altitudes for extended durations while supporting next-generation communication services [49–51]. Together, these projects illustrate the progressive evolution of aerodynamic HAPS from experimental concepts to viable

Table 2.1 The Aerodynamic HAPS projects.

Reference	Project Name	Organization	Period	Country
[43]	SHARP	CRC	1980–1987	Canada
[44]	Pathfinder, Centurion, Helios	NASA ERAST	1994–2003	USA
[45]	Zephyr S	Airbus Defence and Space	2013–Now	United Kingdom
[46–48]	Aquila	Facebook	2014–2018	United Kingdom
[49]	HAWK30	HAPSMobile	2017–Now	Japan
[50, 51]	PHASA-35	BAE Systems	2018–Now	United Kingdom

aerial communication infrastructures for future wireless networks. Table 2.1 shows the aerodynamic HAPS projects.

2.1.1.2 Aerostatic HAPS

Aerostatic HAPS platforms represent an alternative technological pathway toward persistent stratospheric communication infrastructures, relying on buoyancy rather than aerodynamic lift to maintain quasi-stationary operation. Early initiatives such as JAPAN Aerospace Exploration Agency (JAXA)’s SkyNet project explored large stratospheric airships of about 200 m length operating near 20 km altitude, targeting multi-year missions with coverage radius approaching 100 km [52–54]. The Communications from Aerial Platform Networks Delivering Broadband Communications for All (CAPANINA) project further advanced this concept by demonstrating broadband connectivity through airship platforms equipped with free-space optical links, achieving data rates of 1.25 Gbps at approximately 23 km altitude while covering a 64 km radius [55]. Subsequent projects have expanded the operational scope of aerostatic HAPS. The Swiss X-station project employs solar-powered airships operating near 21 km altitude with payload capacities around 100 kg and coverage diameters reaching up to 1000 km, supporting diverse services including telecommunications and remote sensing [56]. Similarly, the Elevate program by Zero 2 Infinity focuses on high-altitude balloon systems capable of transporting payloads of up to 100 kg to altitudes between 18 and 22 km for research and experimental missions [57]. One of the most widely known projects is Alphabet’s Loon project, which deployed networks of high-altitude balloons operating between 18 and 23 km to deliver connectivity to

Table 2.2 The Aerostatic HAPS projects.

Reference	Project Name	Organization	Period	Country
[52–54]	SkyNet	JAXA	1998–2005	Japan
[55]	CAPANINA	University of York	2003–2006	United Kingdom
[56]	X-station	StraXX	2005–Now	Switzerland
[57]	Elevate	Zero 2 Infinity	2009–Now	Spain
[58]	Loon	Alphabet Inc. (previously Google X)	2011–2021	USA
[59]	Stratobus	Thales Alenia Space	2014–Now	France

underserved regions, accumulating over a million flight hours and serving hundreds of thousands of users worldwide [58]. More recently, the Stratobus platform developed by Thales Alenia Space targets long-duration stratospheric airship missions of up to five years, supporting payloads of several hundred kilograms for applications such as Fifth-generation Mobile Network (5G) telecommunications over coverage diameters approaching 500 km [59]. Together, these initiatives demonstrate the growing maturity of aerostatic HAPS technologies and their potential to provide persistent, wide-area communication infrastructures for future wireless networks. Table 2.2 shows the aerostatic HAPS projects.

2.1.1.3 Aerodynamic HAPS Versus Aerostatic HAPS

Aerodynamic and aerostatic HAPS embody two complementary design paradigms for stratospheric platforms, each balancing mobility, endurance, payload capacity, and deployment complexity. Aerodynamic HAPS offers superior maneuverability and flexible deployment, making them particularly suitable for temporary or rapidly deployable missions such as emergency communications [42]. In contrast, aerostatic HAPS, based on airships or balloons, prioritize persistence and payload capacity, enabling long-duration operation and supporting services such as wide-area connectivity, edge computing, and coordination of autonomous systems [27]. Consequently, the choice between aerodynamic and aerostatic HAPS ultimately reflects a fundamental trade-off between mobility and persistence in high-altitude communication platforms.

2.1.2 RIS-assisted Networks

RIS has recently emerged as a promising technology capable of fundamentally transforming the role of the wireless propagation environment in communication systems [16–20]. Unlike conventional wireless networks, where the environment is treated as an uncontrollable medium that causes attenuation, scattering, and interference, RIS enables programmable control over electromagnetic wave propagation [60–62]. These surfaces, typically composed of electromagnetic meta-materials integrated with controllable electronic circuits, can dynamically manipulate the phase, amplitude, or polarization of incident signals. By enabling intelligent manipulation of electromagnetic interactions across the network, RIS allows telecommunication operators to actively shape the wireless environment rather than passively adapt to it. This capability has led to the emerging concept of *smart radio environments*, where the surrounding physical space becomes an intelligent and adaptive component of the communication system [60–62]. As future wireless networks increasingly evolve toward software-defined and adaptive architectures, RIS offers a powerful mechanism to transform the wireless environment into a controllable and cooperative entity [60]. Fig. 2.6 illustrates a typical RIS-assisted communication scenario where the transmitter and receiver are connected through a reflected path in the presence of blockage. The RIS is considered to be implemented as a rectangular planar surface with physical dimensions a and b , which represent the length and width, respectively. The surface is composed of a large number of nearly passive reflecting elements arranged on a regular grid. Let d_x and d_y denote the horizontal and vertical dimensions of each RIS element, respectively. In practical implementations, these element sizes are typically chosen within the range $[\frac{\lambda_c}{10}, \frac{\lambda_c}{5}]$, where $\lambda_c = \frac{c_0}{f_c}$ denotes the carrier wavelength, f_c is the carrier frequency, and c_0 represents the speed of light. Under this configuration, the RIS can be viewed as a two dimensional array of controllable reflecting elements. The surface contains $P = \left\lceil \frac{a}{d_x} \right\rceil$ columns and $Q = \left\lceil \frac{b}{d_y} \right\rceil$ rows of elements, resulting in a total of $M = PQ$ programmable units that collectively shape the propagation environment through controllable phase shifts [61]. This geometric representation provides a convenient abstraction for modeling RIS-assisted wireless channels.

RIS introduces a programmable propagation mechanism in which the wireless channel can be shaped by controlling the phase response of a large number of nearly passive reflecting elements. Consider a transmitter–receiver pair assisted by an RIS composed of M reflecting elements distributed on a planar surface. The equivalent baseband channel between the transmitter and the receiver can be expressed as the

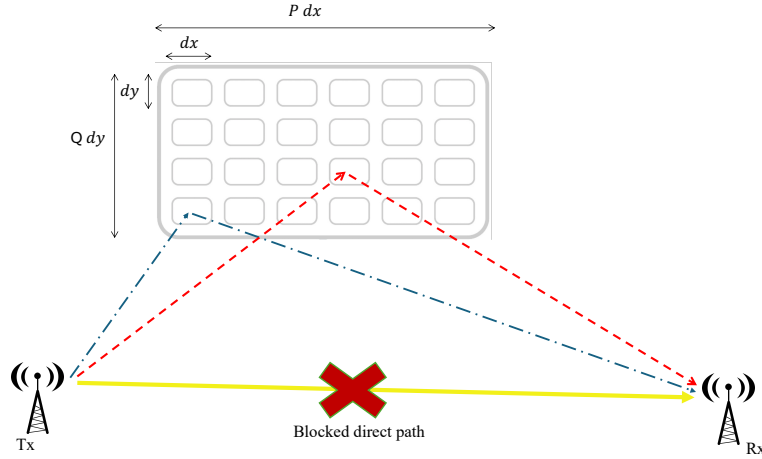


Fig. 2.6 The geometry of connecting the transmitter and receiver via RIS through blockage.

superposition of the direct propagation path and the RIS-reflected paths. Accordingly, the overall channel response can be written as [60, 61]

$$h_{\text{eq}} = h_d + \mathbf{h}_r^T \mathbf{\Theta} \mathbf{h}_t, \quad (2.5)$$

where $h_d \in \mathbb{C}$ denotes the direct channel between the transmitter and the receiver. The vector $\mathbf{h}_t = [h_1^t, h_2^t, \dots, h_M^t]^T \in \mathbb{C}^M$ represents the channel from the transmitter to the RIS, where h_m^t denotes the channel coefficient between the transmitter and the m^{th} RIS element. Similarly, $\mathbf{h}_r = [h_1^r, h_2^r, \dots, h_M^r]^T \in \mathbb{C}^M$ denotes the channel from the RIS to the receiver, where h_m^r represents the propagation coefficient from the m^{th} RIS element to the receiver. The matrix $\mathbf{\Theta} \in \mathbb{C}^{M \times M}$ characterizes the programmable response of the RIS and is typically modeled as a diagonal reflection matrix [60, 61]

$$\mathbf{\Theta} = \text{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \dots, \beta_M e^{j\theta_M}), \quad (2.6)$$

where $\theta_m \in [0, 2\pi)$ denotes the controllable phase shift of the m^{th} RIS element, and $\beta_m \in [0, 1]$ represents the corresponding reflection amplitude coefficient. In ideal passive RIS implementations, β_m is typically close to unity, indicating nearly lossless reflection. Substituting (2.6) into (2.5), the cascaded RIS-assisted channel can be expressed in element-wise form as [60, 61]

$$h_{\text{eq}} = h_d + \sum_{m=1}^M h_m^r \beta_m e^{j\theta_m} h_m^t. \quad (2.7)$$

Equation (2.7) highlights the cascaded structure of RIS-assisted propagation, where each reflected signal component experiences two successive wireless links, i.e., the transmitter-to-RIS link and the RIS-to-receiver link. Let $d_{t,m}$ and $d_{m,r}$ denote the distances from the transmitter to the m^{th} RIS element and from that element to the receiver, respectively. Under typical far-field propagation conditions, the path loss associated with the cascaded link can be approximated as [60, 61]

$$L_m \propto \frac{1}{d_{t,m}^2 d_{m,r}^2}, \quad (2.8)$$

which reflects the characteristic double path-loss effect resulting from the two-hop reflection mechanism. By appropriately configuring the phase shifts $\{\theta_m\}_{m=1}^M$, the reflected signals from different RIS elements can be coherently combined at the receiver. This effectively enables passive beamforming, whereby the RIS shapes the propagation environment to enhance the equivalent channel gain, extend coverage, and provide additional spatial degrees of freedom that can be exploited in system-level design and optimization.

A key advantage of RIS technology lies in its remarkable energy efficiency compared to conventional relay-based communication. Unlike traditional relays that rely on active radio-frequency chains and power amplifiers, RIS operates through nearly passive reflection, enabling intelligent signal redirection with very low power consumption. As a result, the power requirements of the RIS control circuitry remain minimal [60]. In addition to its low power consumption, RIS-assisted communication can reduce the transmission delay associated with conventional relay-based communication, since signal reflection occurs without intermediate decoding, amplification, or forwarding operations. The passive nature of RIS also leads to simpler hardware architectures and avoids issues such as noise amplification and self-interference that typically affect active relay systems. These properties make RIS particularly attractive for energy-constrained platforms, especially non-terrestrial nodes, where lower communication energy consumption can support longer operation time [21]. Moreover, it has been shown that when equipped with a sufficiently large number of reflecting elements, RIS-assisted systems can outperform conventional relay systems in terms of energy efficiency [63].

While terrestrial RIS deployments are often constrained by obstacles, limited coverage, and practical installation challenges, placing RIS on non-terrestrial platforms introduces a new level of architectural flexibility. Deploying terrestrial RIS on ground structures typically requires identifying suitable installation sites, negotiating site

rentals, and obtaining consent from property owners, which can significantly restrict deployment. In contrast, mounting RIS on aerial platforms enables far more flexible and rapid deployment, particularly in locations where terrestrial infrastructure is difficult or impractical to install. Moreover, terrestrial RIS installations usually manipulate signals within a restricted spatial region where the transmitter and receiver lie on the same side of the reflecting surface. Non-terrestrial RIS, however, can offer a near 360-degree panoramic reflection capability, enabling signal redirection between geographically distributed ground nodes. In addition, the elevated position of non-terrestrial RIS substantially increases the probability of establishing LoS links, thereby mitigating blockage effects while enabling significantly wider coverage areas. These characteristics position non-terrestrial RIS as a powerful mechanism for extending coverage and improving connectivity in future wireless networks [21, 37]. HAPS-RIS emerges as a particularly promising realization of non-terrestrial RIS, offering distinct advantages over alternative platforms such as RIS-enabled Satellite (Satellite-RIS) and RIS-enabled UAV (UAV-RIS) [27, 28, 64]. Fig. 2.7 illustrates the rationale and decision roadmap that motivate the selection of HAPS-RIS as the most suitable candidate among alternative deployment options.

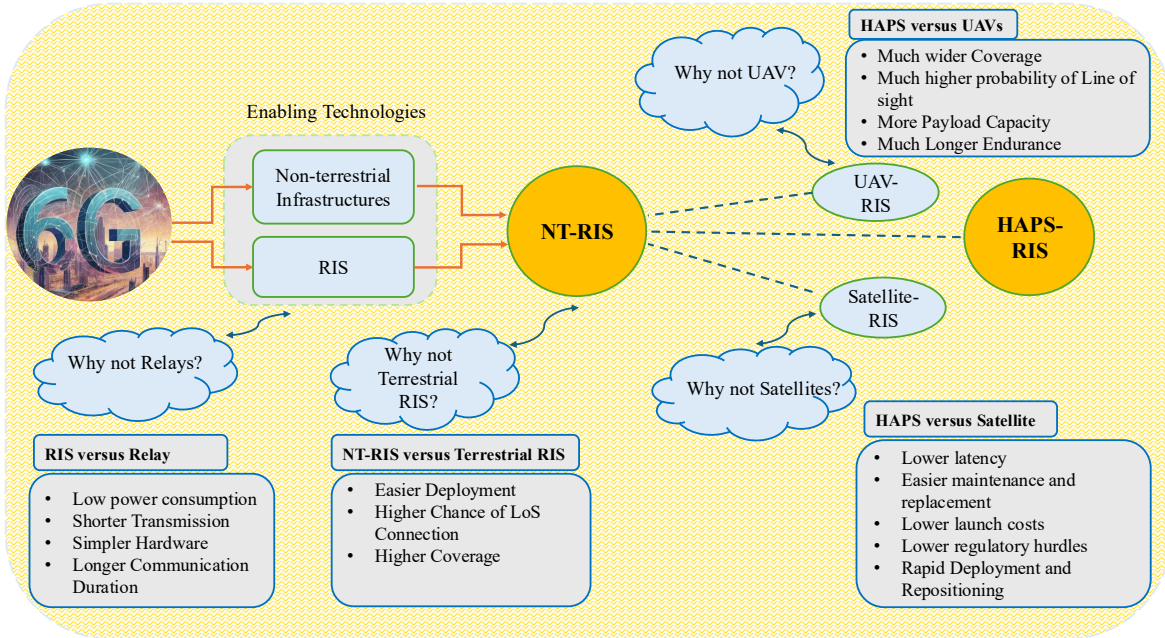


Fig. 2.7 Motivations and contributions of this chapter at a glance.

2.1.3 HAPS-RIS-assisted Networks

While the preceding discussion establishes HAPS-RIS as a particularly promising realization of non-terrestrial RIS architectures, understanding its potential requires examining how this concept has been explored in the existing literature. Over the past few years, a growing body of research has begun to investigate the integration of RIS with HAPS platforms, exploring different system models, optimization strategies, and performance objectives. However, these studies vary significantly in their architectural assumptions, design variables, and system constraints. To provide a structured view of this emerging research direction, Table 2.3 presents a taxonomy of existing HAPS-RIS assisted networks according to several key design dimensions, including HAPS mobility, integration with UAV networks, optimization framework, objectives, variables, and constraints. This classification not only highlights the main directions pursued in the literature but also reveals several important gaps that motivate the architectural and optimization frameworks developed in this thesis.

As shown in the table, most existing works consider HAPS-RIS systems under simplified architectural assumptions. Early studies on HAPS-RIS systems primarily concentrate on analytical characterization of the communication link and fundamental performance limits. For instance, [28] establishes the basic feasibility of HAPS-RIS communication by analyzing the received signal power through a link-budget formulation, where the HAPS location is treated as the key design variable under physical propagation constraints. Building on this analytical perspective, several subsequent works investigate reliability-related metrics. In particular, [68] and [69] study the outage probability of HAPS-RIS links by optimizing RIS phase shifts under system-level parameters and outage thresholds. Similarly, [71] analyzes outage probability and bit-error rate by incorporating additional system uncertainties such as HAPS orientation variations and position deviations. Beyond analytical performance evaluation, another line of research formulates optimization problems to improve network performance by jointly configuring communication resources and RIS parameters. For example, [65] proposes a joint optimization that simultaneously adjusts Control Station (CS) transmit power and RIS configuration to balance throughput and fairness among users under QoS constraints. This direction is further extended in [66], where resource efficiency is maximized through joint optimization of user association, CS power allocation, and RIS phase shifts while considering system constraints such as HAPS platform size and QoS requirements. Similarly, [70] focuses on maximizing both sum-rate and energy efficiency by optimizing user transmit power and RIS

Table 2.3 Taxonomy of HAPS-RIS assisted networks.

Ref	Mobile HAPS	UAV Integration Level	Framework	Objectives	Variables	Constraints
[28]	✗	✗	Analytical	Received power	HAPS location	Physical link-budget
[65]	✗	✗	Joint	Throughput, fairness, RIS-unit	CS power, RIS parameters	QoS, CS power, RIS-size, and phase
[66]	✗	✗	Joint	Resource efficiency	User association, CS power, RIS phase shifts	QoS, CS power, HAPS size, phase shifts
[67]	✗	✗	Single objective	Channel estimation error	Learning model parameters	Pilot overhead; hardware impairments
[68]	✗	✗	Analytical	Outage probability	RIS phase shifts, system parameters	outage threshold, single-antenna nodes
[69]	✗	✗	Analytical	Outage probability	RIS phase shifts, system parameters	THz impairments, outage threshold, single-antenna nodes
[70]	✗	✗	Joint, single-objective	Sum-rate, energy-efficiency	user transmit power, RIS parameters	Minimum QoS per user; total CS power; HAPS size
[71]	✗	✗	Analytical	Outage probability and bit error rate	RIS phase shifts; system parameters	HAPS orientation, position deviation
[72]	✗	As user	Single-objective	Secrecy rate	RIS phase shifts	Finite phase resolution
[73]	✗	As user	Joint Single objective	Secrecy rate	RIS phase shifts, beamforming vector	BS transmit beamforming vector, phase constraints
[74]	✗	As user	Analytical	Evaluate average harvested energy at UAV	RIS size, power parameters	RIS vibration, LoS requirement
Thesis Chapter 3	✓	✗	Multi-objective, closed-form	Channel gain; Delay-Doppler spread	RIS phase shifts	Causality of phase shifts
Thesis Chapter 4	✗	As Infrastructure	Multi-objective, Hierarchical	HAPS-RIS users; number of UAVs	UAV number; zone association	Rate requirements
Thesis Chapter 5	✗	As Infrastructure	Multi-objective, Joint	HAPS-RIS users; UAV Number; Average total UAV path loss	UAV location & number; RIS phase shifts; subcarrier allocation; user association; RIS element assignment	Rate requirements; power budgets; exclusive association; OFDMA constraints

parameters subject to QoS guarantees and power budget limitations. In addition to throughput-oriented optimization, several studies address specialized communication objectives within the HAPS-RIS framework. For instance, [67] investigates learning-based channel estimation techniques for HAPS-RIS systems, where the objective is to minimize channel estimation error while accounting for pilot overhead and hardware impairments. Security-oriented designs are considered in [72] and [73], where the RIS phase shifts and beamforming vectors are optimized to maximize secrecy rate under constraints such as finite phase resolution and beamforming limitations at the base station. Furthermore, [74] explores wireless energy transfer in HAPS-RIS systems by evaluating the average harvested energy at UAV receivers, where RIS size and transmit power parameters are optimized under practical constraints including RIS vibration and LoS requirements. Despite the diversity of objectives and methodologies explored in the existing literature, a closer inspection of Table 2.3 reveals several important structural limitations in current HAPS-RIS research. Aerodynamic HAPS offer superior maneuverability and flexible deployment, making them particularly suitable for temporary or rapidly deployable missions such as emergency communications [42]. However, despite these advantages, none of the existing works summarized in Table 2.3 investigate RIS integration with mobile aerodynamic HAPS platforms. To address this gap, Chapter 3 of this thesis introduces a novel aerodynamic HAPS-RIS architecture and proposes a multi-objective framework that captures the fundamental trade-off between channel gain and delay-Doppler spread in mobile stratospheric communication links. In contrast, aerostatic HAPS platforms prioritize persistence and payload capacity, enabling long-duration operation [27]. These characteristics make aerostatic HAPS particularly attractive as auxiliary infrastructures capable of assisting other non-terrestrial networks. One particularly promising application is the support of UAV-assisted networks, where UAVs operate as aerial base stations but face inherent limitations in coverage and endurance. Nevertheless, the existing literature has not explored how aerostatic HAPS-RIS platforms can assist UAV-based networks in such scenarios. Chapter 4 of this thesis addresses this unexplored direction by introducing a novel network architecture where an aerostatic HAPS-RIS assists UAV base stations to enhance network coverage while minimizing the number of required UAVs. Building upon this architecture, Chapter 5 further advances the design by proposing a fully integrated joint multi-objective framework that simultaneously optimizes UAV deployment, RIS configuration, resource allocation, and user association. This unified framework represents the culmination of the proposed architectures and establishes a

comprehensive design methodology for integrated HAPS-RIS and UAV-based wireless networks.

2.1.4 UAVs in the Action

The preceding discussion highlights that aerostatic HAPS-RIS platforms can provide a stable stratospheric layer capable of supporting and coordinating lower-altitude UAV networks. Fig. 2.8 shows the scenario where aerostatic HAPS-RIS can be used as auxiliary infrastructure to assisted UAVs that operate as aerial base stations. While the architectural role of UAVs within such integrated aerial systems will be studied in detail in Chapters 4 and 5, it is essential to establish the underlying propagation model that governs UAV-assisted communication links. Unlike the HAPS channel, which is predominantly characterized by deterministic LoS propagation due to the stratospheric operating altitude, UAV communication typically occurs at lower altitudes where environmental blockages introduce both LoS and Non-Line of Sight (NLoS) propagation conditions. Consequently, the UAV channel is commonly modeled through a probabilistic LoS formulation that captures the dependence of the propagation state on the geometric configuration of the UAV and the ground users [7–15].

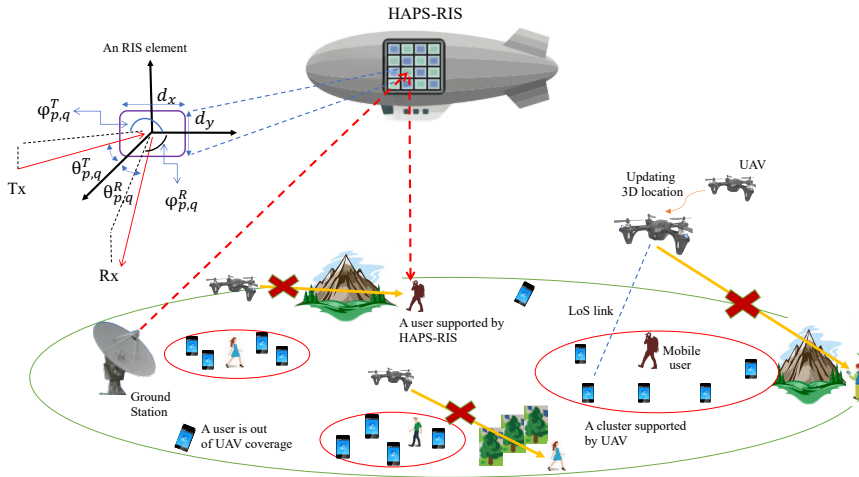


Fig. 2.8 Heterogeneous infrastructures: Aerostatic HAPS-RIS and UAVs.

Let the three dimensional position of UAV j and the ground user i be denoted by $\mathbf{r}_j^{\text{UAV}} = (x_j^{\text{UAV}}, y_j^{\text{UAV}}, z_j^{\text{UAV}})$ and $\mathbf{r}_i = (x_i, y_i, z_i)$, respectively. The distance between UAV j and user i is therefore given by

$$d_{ij} = \|\mathbf{r}_j^{\text{UAV}} - \mathbf{r}_i\| = \sqrt{(x_j^{\text{UAV}} - x_i)^2 + (y_j^{\text{UAV}} - y_i)^2 + (z_j^{\text{UAV}} - z_i)^2}. \quad (2.9)$$

To capture the propagation geometry, the elevation angle from user i toward UAV j can be written as [13]

$$\tilde{\theta}_{ij} = \frac{180}{\pi} \arcsin \left(\frac{z_j^{\text{UAV}} - z_i}{d_{ij}} \right), \quad (2.10)$$

which plays a key role in determining the probability that the propagation path remains unobstructed. The LoS probability between UAV j and user i is expressed as [13]

$$P_{ij,\text{LoS}}^{\text{UAV}} = \frac{1}{1 + \psi \exp \left[-\beta \left(\tilde{\theta}_{ij} - \psi \right) \right]}, \quad (2.11)$$

where β and ψ are environment-dependent parameters. The probability of a NLoS link is $P_{ij,\text{NLoS}}^{\text{UAV}} = 1 - P_{ij,\text{LoS}}^{\text{UAV}}$. Under this probabilistic propagation framework, the average large-scale path loss of the UAV-user link can be expressed as [13]

$$\bar{L}_{ij} = P_{ij,\text{LoS}}^{\text{UAV}} \eta_1 \left(\frac{4\pi f_c}{c_0} d_{ij} \right)^\alpha + P_{ij,\text{NLoS}}^{\text{UAV}} \eta_2 \left(\frac{4\pi f_c}{c_0} d_{ij} \right)^\alpha, \quad (2.12)$$

where f_c denotes the carrier frequency, c_0 is the speed of light, α is the path-loss exponent, and η_1 and η_2 represent the excessive attenuation factors associated with LoS and NLoS propagation conditions, respectively. Accordingly, the effective channel gain between UAV j and user i can be written as [13]

$$h_{ij}^{\text{UAV}} = \sqrt{G_j^{\text{UAV}} G_i \bar{L}_{ij}^{-1}}, \quad (2.13)$$

where G_j^{UAV} and G_i denote the antenna gains of UAV j and user i , respectively. This representation captures the essential propagation characteristics of UAV-assisted communication and provides a tractable abstraction for the system-level optimization frameworks developed in Chapters 4 and 5.

2.1.5 Why Multi-objective Vision is Needed?

Redesigning wireless network architectures for next-generation systems cannot be achieved by considering individual technologies in isolation. Instead, it requires the coordinated integration of multiple enabling technologies, each introducing new controllable dimensions in the network architecture. The integration of emerging enabling technologies, e.g., HAPS and RIS, further expands the architectural design space by introducing new controllable dimensions in network topology, propagation environments, and resource allocation. While this integration significantly expands

the design space and unlocks unprecedented degrees of freedom, it simultaneously introduces a set of inherently conflicting objectives [6, 75, 76]. Consequently, the architectural redesign problem becomes fundamentally multi-dimensional and cannot be effectively addressed through traditional single-objective design principles. A multi-objective vision is therefore essential to simultaneously capture these competing objectives and to systematically explore the trade-offs that arise when integrating diverse enabling technologies into a unified network architecture [6, 75, 76]. The following section introduces the multi-objective visions that provide the theoretical foundation for navigating these trade-offs and for redesigning wireless architectures.

2.2 Multi-objective Vision

Motivated by the discussion in the previous section on the necessity of adopting a multi-objective perspective to redesign the wireless network architectures, this section further elaborates on this vision by introducing the fundamental principles of multi-objective optimization. Traditional optimization frameworks typically select one performance metric as the primary objective while incorporating the remaining metrics as constraints. Although this approach simplifies the mathematical formulation, it assumes that appropriate bounds for the secondary objectives can be determined in advance. In large-scale communication systems, however, these relationships are rarely known beforehand due to the complex interactions among system components. Multi-objective optimization provides a framework for involving multiple objectives within a unified setting, enabling the systematic analysis of trade-offs among competing performance criteria [6, 77–80].

Consider a multi-objective optimization problem involving K performance objectives whose values depend on a set of design variables belonging to a feasible decision space. Let the global decision vector be denoted by $\mathbf{z} \in \mathcal{Z}$, where $\mathcal{Z} \subseteq \mathbb{R}^n$ represents the feasible set and $\mathbb{R}^n$ is n -dimensional real space. The multi-objective optimization problem can then be written as [75, 78]

$$\max_{\mathbf{z} \in \mathcal{Z}} \mathbf{g}(\mathbf{z}) = [g_1(\mathbf{z}), g_2(\mathbf{z}), \dots, g_K(\mathbf{z})]^T, \quad (2.14)$$

where $g_k : \mathcal{Z} \rightarrow \mathbb{R}$ denotes the k^{th} objective function and K is the total number of objectives. In large-scale system design problems, the decision variables exhibit an inherent structural decomposition reflecting the architecture of the underlying system. In particular, the global decision vector can be partitioned into a set of shared

variables that jointly influence multiple objectives and a set of objective-specific variables associated with individual subsystems. Accordingly, the decision vector can be expressed as [75, 78]

$$\mathbf{z} = [\mathbf{x}^T, \mathbf{y}_1^T, \mathbf{y}_2^T, \dots, \mathbf{y}_K^T]^T, \quad (2.15)$$

where $\mathbf{x} \in \mathcal{X} \subseteq \mathbb{R}^{n_0}$ denotes the set of shared decision variables that couple multiple objectives, while $\mathbf{y}_k \in \mathcal{Y}_k \subseteq \mathbb{R}^{n_k}, \forall k = 1, \dots, K$, represents the variables specific to the k th objective. Under this representation, the feasible set naturally factorizes as

$$\mathcal{Z} = \mathcal{X} \times \mathcal{Y}_1 \times \dots \times \mathcal{Y}_K. \quad (2.16)$$

The k^{th} objective function can then be written as $g_k(\mathbf{x}, \mathbf{y}_k), \forall k = 1, \dots, K$, which highlights that each objective depends both on its own subsystem variables and on the shared variables that capture interactions among different components of the system.

Pareto dominance. Since the objective function is vector-valued, feasible solutions cannot generally be ordered using a single scalar criterion. Instead, optimality is defined through the concept of *Pareto dominance*. Consider two feasible solutions $\mathbf{z}_1, \mathbf{z}_2 \in \mathcal{Z}$. Solution $\mathbf{z}_1$ is said to Pareto dominate $\mathbf{z}_2$, denoted by $\mathbf{z}_1 \succ \mathbf{z}_2$, if

$$g_k(\mathbf{z}_1) \geq g_k(\mathbf{z}_2), \quad \forall k \in \mathcal{K}, \quad (2.17)$$

with strict inequality for at least one objective, i.e.,

$$\exists j \in \mathcal{K} \text{ such that } g_j(\mathbf{z}_1) > g_j(\mathbf{z}_2). \quad (2.18)$$

In other words, a solution dominates another if it performs no worse in all objectives while improving at least one of them [75, 78].

Pareto optimal. Based on this notion, a feasible solution $\mathbf{z}^* \in \mathcal{Z}$ is said to be *Pareto optimal* if it is not dominated by any other feasible solution. Formally, $\mathbf{z}^*$ is Pareto optimal if there exists no $\mathbf{z} \in \mathcal{Z}$ such that $\mathbf{z} \succ \mathbf{z}^*$. Equivalently, $\mathbf{z}^*$ is Pareto optimal if no feasible solution can improve at least one objective without degrading at least one of the remaining objectives [75, 78].

Pareto optimal set. The set of all Pareto optimal solutions is referred to as the *Pareto optimal set* and is defined as [75, 78]

$$\mathcal{Z}^* = \{\mathbf{z} \in \mathcal{Z} \mid \nexists \mathbf{z}' \in \mathcal{Z} \text{ such that } \mathbf{z}' \succ \mathbf{z}\}. \quad (2.19)$$

Pareto frontier. Mapping Pareto optimal set into the objective space yields the *Pareto frontier*, given by [75, 78]

$$\mathcal{F}^* = \{\mathbf{g}(\mathbf{z}) \mid \mathbf{z} \in \mathcal{Z}^*\}. \quad (2.20)$$

The Pareto frontier therefore characterizes the attainable trade-offs among the competing objectives.

Pareto boundary. Let the attainable objective set be defined as [75, 78]

$$\mathcal{F} = \{\mathbf{g}(\mathbf{z}) \in \mathbb{R}^K \mid \mathbf{z} \in \mathcal{Z}\}, \quad (2.21)$$

which represents all achievable objective vectors corresponding to feasible decisions. The *Pareto boundary* is defined as the subset of $\mathcal{F}$ consisting of points that cannot be improved in any objective without degrading at least one other objective. Formally, it can be expressed as

$$\partial\mathcal{F}^* = \{\mathbf{g}(\mathbf{z}) \in \mathcal{F} \mid \nexists \mathbf{z}' \in \mathcal{Z} \text{ such that } \mathbf{g}(\mathbf{z}') \succ \mathbf{g}(\mathbf{z})\}. \quad (2.22)$$

In other words, the Pareto boundary represents the boundary of the attainable objective region corresponding to Pareto-efficient solutions. Geometrically, it forms the envelope of optimal trade-offs among the objectives and coincides with the Pareto frontier in the objective space. Consequently, multi-objective optimization does not seek a single globally optimal solution. Instead, it relies on the concept of Pareto dominance to identify the set of Pareto-optimal solutions in the decision space and their corresponding image in the objective space, forming the Pareto frontier and boundary. These structures capture the attainable trade-offs among competing objectives and provide the basis for selecting suitable operating points according to the underlying system design priorities [75, 78].

From architectural perspective, multi-objective frameworks can be categorized into disjoint and joint paradigms. In disjoint approach, the design problem is decomposed into multiple subproblems associated with different subsystems or architectural layers.

Each subsystem solves a local optimization problem while treating the outputs of other subsystems as fixed parameters. Such formulations arise naturally in hierarchical systems where decisions are made at multiple levels. Although this decomposition improves scalability and computational tractability, it may limit the ability to capture global interactions across subsystems. In contrast, joint paradigm integrate all relevant design variables into a single unified optimization framework. By jointly optimizing the entire system, the global trade-offs across subsystems and performance objectives can be explored. However, the the joint paradigms are typically high-dimensional and computationally demanding, particularly when large-scale network architectures are considered. These considerations become particularly significant in the context of emerging wireless network architectures integrating NTN and RIS technologies. The integration of these enabling technologies introduces new controllable dimensions in network topology, propagation environments, and infrastructure deployment. While these capabilities significantly expand the architectural design space, they also introduce complex interactions among performance metrics which need to be studied as multi-objective vision.

2.3 Lessons Learned and Conclusion

This chapter reveals that the evolution of wireless networks is no longer driven solely by incremental improvements in communication technologies, but by the emergence of new architectural degrees of freedom. Enabling technologies, e.g., NTN and RIS, can fundamentally expand the architectural design space of wireless networks. However, this expansion introduces an inherent tension among competing system objectives. Consequently, redesigning future wireless network architectures becomes intrinsically a multi-objective problem. In this context, enabling technologies act as mechanisms that expand the design space, while multi-objective optimization frameworks provide the methodological tools required to navigate the resulting trade-offs. The literature further indicates that most existing studies investigate these technologies in isolation. Such fragmented perspectives fail to capture the architectural implications of integrating these technologies within a multi-objective framework. The subsequent chapters of this thesis investigate the redesign of wireless network architectures through the coordinated integration of enabling technologies. Chapter 3 proposes a multi-objective framework for aerodynamic HAPS-RIS systems, revealing the dynamic propagation characteristics of non-terrestrial programmable surfaces. Chapter 4 investigates the architectural potential of aerostatic HAPS platforms in supporting UAV networks, in a hierarchical framework, analyzing their role in expanding coverage and deployment efficiency. Finally, Chapter 5 proposes a unified multi-objective optimization framework for integrated HAPS-RIS and UAV networks, where infrastructure placement, propagation control, and resource allocation are jointly optimized. Together, these investigations address the fundamental gap identified in this chapter.

Chapter 3

Connect the Unconnected with Aerodynamic HAPS-RIS

This chapter initiates the first technical contribution of the PhD thesis and transforms the conceptual gaps identified in chapter 2 into a concrete architectural investigation. The motivation behind exploiting aerodynamic HAPS is fully studied in chapter 2. The advantages of exploiting aerodynamic over aerostatic HAPS in wireless networks are low-cost and swift deployment and high resilience to turbulence [27]. These features make aerodynamic HAPS a promising candidate technology in the move towards integration of terrestrial and non-terrestrial networks [27]. Although the advantages of using aerodynamic HAPS-RIS are clarified, time-varying effects can pose major challenges in this scenario. Consequently, the main research question that arises is “*How can wireless network architectures be redesigned through aerodynamic HAPS-RIS platforms to provide connectivity for unconnected ground stations under time-varying channels?* ” which is fully addressed in this chapter. To the best of my knowledge, based on the literature surveyed in this thesis, no prior study has been found to investigate a wireless network architecture enabled by aerodynamic HAPS-RIS. The motivations, challenges, and contributions of this chapter are shown at a glance in Fig. 3.1. This technical contribution is published in IEEE Wireless Communications Letters (WCL).

3.1 The Main Contributions of this Chapter

The main contributions of this technical chapter can be summarized as

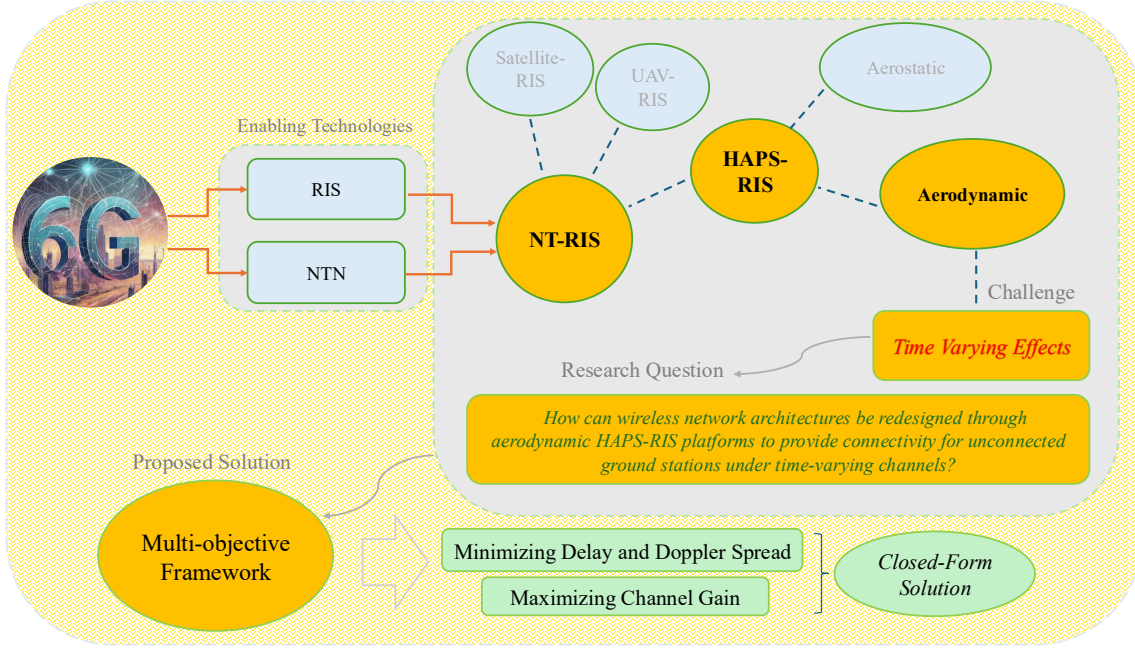


Fig. 3.1 Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.

- We introduce a *novel network architecture* for NT-RIS assisted networks. We propose a new system model where RIS is mounted on aerodynamic HAPS to connect the unconnected terrestrial ground stations in emergency situations thanks to the aforementioned significant features of aerodynamic HAPS.
- We *mathematically model the mobility pattern of each RIS element* based on the dimensions of the RIS and the RIS elements, and the predictive trajectory of the aerodynamic HAPS-RIS. Next, We obtain a geometrical model for all the channel metrics and time-varying effects. To the best of my knowledge, based on the literature surveyed in this thesis, no prior work has geometrically modelled the mobility profile of a mobile RIS using these parameters.
- We propose a multi-objective optimization framework where the objective functions are the channel gain, the delay spread upper bound and the Doppler spread. We *obtain a closed-form solution* for the RIS phase shifts, by introducing a reference RIS element, adopting Pareto optimality. The obtained closed-form is based on the known locations of the transmitter and the receiver, and the known time-varying position of the aerodynamic HAPS-RIS, thanks to knowing its mobility pattern. This leads to practical and simple implementation as the

RIS phase shifts can be efficiently calculated by the onboard processing unit on HAPS.

3.2 The Proposed Network

In this chapter, We consider a heavy blockage scenario where the link between the terrestrial transmitter (Tx) and receiver (Rx) is blocked. We consider the network architecture in Fig. 3.2, exploiting aerodynamic HAPS-RIS to connect the ground stations. We consider the RIS to be a rectangle with the length a and the width b , which is located on the bottom of the HAPS in the xy -plane. d_x and d_y are the dimensions of each RIS element, which are in the range of $[\frac{\lambda_c}{10}, \frac{\lambda_c}{5}]$ where $\lambda_c = \frac{c_0}{f_c}$ is the wavelength [61]. f_c is the carrier frequency and c_0 is the speed of light. The RIS consists of $P = \lceil \frac{a}{d_x} \rceil$ columns and $Q = \lceil \frac{b}{d_y} \rceil$ rows of reflecting elements. The aerodynamic HAPS has a circular movement in the stratosphere with radius R_0 centered at the origin of the Cartesian coordinate system and the velocity v . It is not practical to consider different trajectories for the aerodynamic HAPS, like what is expected for UAVs. It is vital to consider the circular trajectory for the aerodynamic HAPS, which leads to quasi-stationary position, that brings resilience to turbulence [27]. As the aerodynamic HAPS is moving with high speed, both sides of the cascade channel for each RIS element are time-varying. This can be clearly observed in Fig. 3.3 which shows the geometrical mobility pattern of RIS elements based on the predictive mobility of the aerodynamic HAPS.

Definition 3.1. *The geometrical mobility pattern of the RIS elements can be attained as a function of the predictive mobility of the aerodynamic HAPS, and the dimensions a , b , d_x , and d_y as*

$$(x_{p,q}(t), y_{p,q}(t), z_{p,q}(t)) = (R_{p,q} \cos(\frac{vt}{R_{p,q}} + \alpha_{p,q}), R_{p,q} \sin(\frac{vt}{R_{p,q}} + \alpha_{p,q}), 0) \quad (3.1)$$

where

$$R_{p,q} = \sqrt{(R_0 - \frac{a}{2} + (p - \frac{1}{2})d_x)^2 + (-\frac{b}{2} + (q - \frac{1}{2})d_y)^2}, \quad (3.2)$$

$$\alpha_{p,q} = \arctan \left(\frac{-\frac{b}{2} + (q - \frac{1}{2})d_y}{R_0 - \frac{a}{2} + (p - \frac{1}{2})d_x} \right). \quad (3.3)$$

We consider a LoS dominated scenario for the links between Tx/Rx and HAPS-RIS as the aerodynamic HAPS-RIS flies in a high altitude, i.e., 20 km [27]. Furthermore, in HAPS-RIS scenarios, the ground stations are considered as high directional antenna

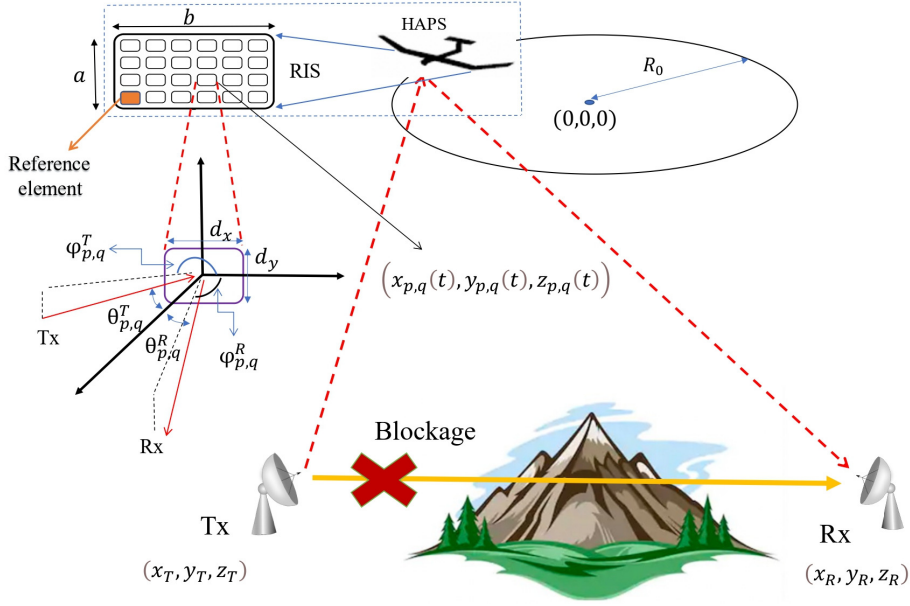


Fig. 3.2 Proposed network architecture based on aerodynamic HAPS-RIS.

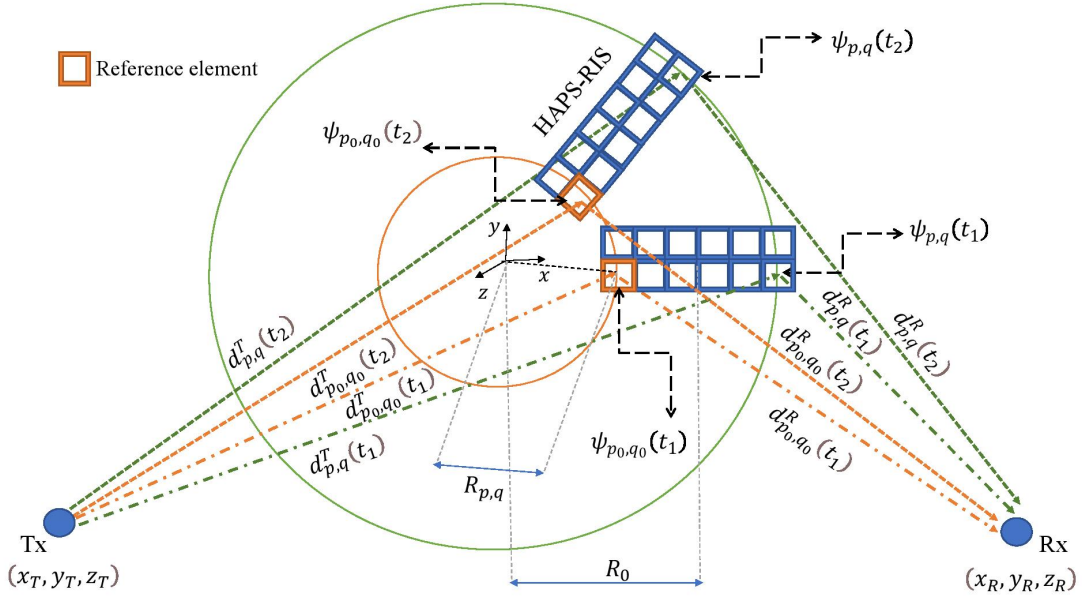


Fig. 3.3 Geometrical mobility pattern of RIS elements based on the predictable mobility of the aerodynamic HAPS.

gain transceivers which leads to establishing strong and dominant LoS link [65, 66]. The Tx sends a passband signal

$$s_p(t) = \sqrt{2}\Re\{s(t)\exp(j2\pi f_ct)\} = \frac{s(t)\exp(j2\pi f_ct) + s^*(t)\exp(-j2\pi f_ct)}{\sqrt{2}}, \quad (3.4)$$

where $s(t)$ is the complex baseband signal with bandwidth $B/2$ which is modulated to the carrier frequency f_c satisfying $B \ll 2f_c$, [60]. Thus, the received baseband signal can be shown as

$$r(t) = \sum_{p=1}^P \sum_{q=1}^Q \Gamma_{p,q}(t) \exp(-j2\pi f_c \tau_{p,q}(t) - j\psi_{p,q}(t)) s(t - \tau_{p,q}(t) - \frac{\psi_{p,q}(t)}{2\pi f_c}) + n(t), \quad (3.5)$$

where $\Gamma_{p,q}(t)$ is the cascade channel gain coefficient for the RIS element (p, q) and $n(t)$ is the additive white Gaussian noise (AWGN). Additionally, $\psi_{p,q}(t)$ is the phase shift of the RIS element (p, q) . Using the Friis model, [41], $\Gamma_{p,q}(t)$ is the multiplication of the ground to air and air to ground amplitude gains as

$$\Gamma_{p,q}(t) = \frac{\lambda_c^2}{16\pi^2 \prod_S d_{p,q}^S(t)} \sqrt{\prod_S g_S^{p,q}(t) \prod_S g_{p,q}^S(t)}, \quad (3.6)$$

where $S \in \{T, R\}$ represents the Tx/Rx. The distance between the RIS element (p, q) and the Tx/Rx can be calculated as

$$d_{p,q}^S(t) = \sqrt{(x_{p,q}(t) - x_S)^2 + (y_{p,q}(t) - y_S)^2 + (z_{p,q}(t) - z_S)^2}, \quad (3.7)$$

Moreover, $g_{p,q}^S(t)$ is the antenna gain of RIS element (p, q) to S , which can be a function of $\theta_{p,q}^S(t) \in [0, \pi]$ and $\varphi_{p,q}^S(t) \in [0, 2\pi]$. We consider that $g_{p,q}^S(t)$ is zero for $\theta_{p,q}^S(t) \in [\frac{\pi}{2}, \pi]$. The elevation angle from the RIS element (p, q) to S is formulated as

$$\theta_{p,q}^S(t) = \arccos\left(\frac{z_S - z_{p,q}(t)}{d_{p,q}^S(t)}\right). \quad (3.8)$$

The azimuth angle from the RIS element (p, q) to S can be shown as

$$\varphi_{p,q}^S(t) = \arctan\left(\frac{y_S - y_{p,q}(t)}{x_S - x_{p,q}(t)}\right). \quad (3.9)$$

Furthermore, $g_S^{p,q}(t)$ is the antenna gain of the Tx/Rx to/from the RIS element (p, q) . The terms $\theta_S^{p,q}(t)$ and $\varphi_S^{p,q}(t)$ are the angle of elevation and azimuth from S to the RIS element (p, q) , respectively. $\tau_{p,q}(t)$ is the cascade path delay for the RIS element (p, q) , which can be formulated as

$$\tau_{p,q}(t) = \frac{\sum_S d_{p,q}^S(t)}{c_0}. \quad (3.10)$$

The instantaneous cascade channel gain as the ratio between the received power, $P_R(t)$, and the time-invariant transmit power, P_T , can be obtained as

$$\frac{P_R(t)}{P_T} = \left| \sum_{p=1}^P \sum_{q=1}^Q \Gamma_{p,q}(t) \exp(-j2\pi f_c \tau_{p,q}(t) - j\psi_{p,q}(t)) \right|^2, \quad (3.11)$$

The time-varying effects caused by the cascade paths through the RIS elements, i.e., the Doppler spread, $B_{Do}(t)$, and the delay spread, $T_{De}(t)$, can be obtained as [60, 81]

$$B_{Do}(t) = f_c \times \max_{p,q,p',q'} \left| \frac{d}{dt}(\tau_{p,q}(t) + \frac{\psi_{p,q}(t)}{2\pi f_c}) - \frac{d}{dt}(\tau_{p',q'}(t) + \frac{\psi_{p',q'}(t)}{2\pi f_c}) \right|, \quad (3.12)$$

$$T_{De}(t) = \max_{p,q} \left\{ \tau_{p,q}(t) + \frac{\psi_{p,q}(t)}{2\pi f_c} \right\} - \min_{p,q} \left\{ \tau_{p,q}(t) + \frac{\psi_{p,q}(t)}{2\pi f_c} \right\}. \quad (3.13)$$

Each cascade path through each RIS element is subject to delay and Doppler shift. When the number of RIS elements is large, the cascade channel becomes a multi-path environment, which can boost the channel gain. However, this introduces additional effects such as Doppler spread and delay spread, which need to be compensated in RIS phase shift design. Alleviating Doppler spread and delay spread at the Rx is considerably more complicated than mitigating Doppler shifts, [60]. Therefore, alleviate the delay and Doppler spread via appropriate RIS phase shift design and leave the Doppler shift mitigation to the Rx side.

The proposed aerodynamic HAPS-RIS framework is developed under several modelling assumptions to enable a tractable analytical framework. The aerodynamic HAPS is assumed to follow a predetermined circular trajectory, representing the controlled and predictable flight behaviour of such platforms. This predictable mobility results in a smooth evolution of the HAPS-RIS-ground geometry, allowing the communication channel to be approximated as locally quasi-stationary within each optimisation interval while preserving its long-term time-varying characteristics. This assumption forms the basis of the proposed geometry-aware RIS phase-shift design. Furthermore, the analysis focuses on the mobility-induced geometric evolution of the cascaded HAPS-RIS channel. Therefore, atmospheric propagation effects, including absorption, rain attenuation, cloud attenuation, and atmospheric turbulence, are not explicitly considered, as they primarily contribute to additional large-scale attenuation and do not alter the proposed geometric formulation. Consequently, the proposed framework is applicable to predictable HAPS flight trajectories, while detailed atmospheric propagation effects and unpredictable trajectory deviations are left for future investigation.

3.3 Proposed Multi-objective Optimization Problem

We consider a multi-objective optimization problem, including analogous objective functions as in [81], to maximize (3.11) while minimizing (3.12) and (3.13) simultaneously. Therefore, the main optimization problem can be formulated as

$$\text{OP} : \max_{\forall p,q,t: \psi_{p,q}(t) \geq 0} \left[\frac{P_R(t)}{P_T}, -B_{\text{Do}}(t), -T_{\text{De}}(t) \right]. \quad (3.14)$$

The feasible set $\psi_{p,q}(t) \geq 0$, originates from the causality requirement [60]. We consider a mobile RIS where both sides of the cascade channel are time-varying while in [81] the RIS is fixed and only one side of the cascade channel is time-varying. Furthermore, We consider the link between Tx and Rx is blocked while in [81] the direct link is available. The adopted technique in [81] does not work for my proposed model to solve OP. To tackle this issue, as can be seen in Fig. 3.3, We consider a single RIS element as a reference with variable phase shift $\psi_{p_0,q_0}(t)$, so that the other phase shifts can be obtained based on that. The cascade path through the reference element is called reference path.

3.4 Proposed RIS Phase Shift Design: Pareto Optimal Solution

To find the optimal solution of OP, let us consider the search space as the set Ψ . Even if We relax the continuous RIS phase shifts to discrete ones with M quantization levels, to simplify the problem, the search space has M^{PQ} states. As this is a massive number for a large number of RIS elements, finding the optimal solution is intractable in terms of computational complexity. For large values of M , to get close to the continuous case, the search space Ψ becomes prohibitively large. Thus, it is evident that if the phase shifts are continuous like my proposed scenario, solving (3.14) is not affordable in terms of computational complexity. To tackle this issue, We find the Pareto optimal solution of OP in *Proposition 3.1* by decomposing OP into OP_1 and OP_2 .

Proposition 3.1. Let us decompose OP into OP_1 and OP_2 as

$$\text{OP}_1 : \forall p, q, t : \psi_{p,q}(t) \in \arg \max_{\Psi} \frac{P_R(t)}{P_T} \cap \arg \min_{\Psi} B_{\text{Do}}(t), \quad (3.15)$$

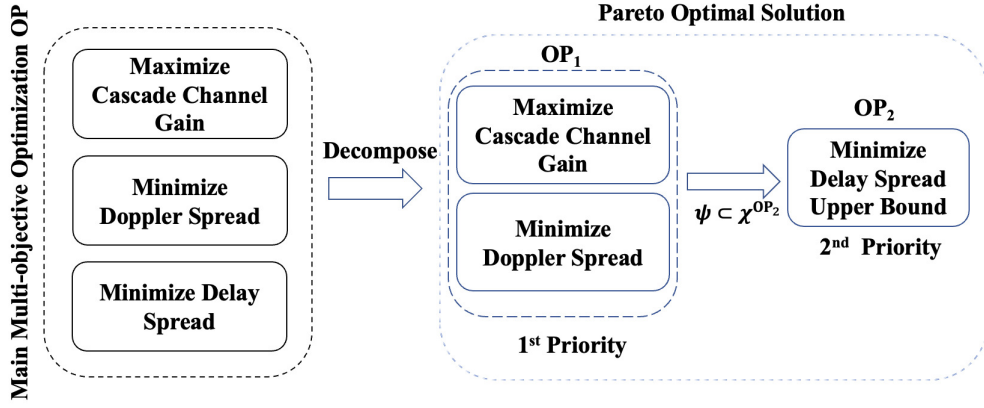


Fig. 3.4 The proposed Pareto Optimal Solution Method

$$\text{OP}_2 : \forall p, q, t : \psi_{p,q}(t) \in \arg \min_{\psi \in \chi^{\text{OP}_2}} T_{\text{De}}^{\text{upp}}(t). \quad (3.16)$$

As OP_1 and OP_2 can not be optimized simultaneously, We consider that OP_1 has the higher priority order compared to OP_2 , which is elaborated later in *Lemma 3.2*. As can be seen in Fig. 3.4, OP_1 optimizes $\frac{P_{\text{R}}(t)}{P_{\text{T}}}$ and $B_{\text{Do}}(t)$ simultaneously. Let us consider all the possible solutions of OP_1 is the solution set χ^{OP_2} which is a feasible set for OP_2 . In OP_2 , We optimize the delay spread upper bound, $T_{\text{De}}^{\text{upp}}(t)$, over the feasible set $\psi \in \chi^{\text{OP}_2}$ resulting from solving OP_1 . The Pareto optimal closed-form solution of (3.14) is

$$\psi_{p,q}(t) = 2\pi \text{mod}(f_c(\tau_{p_0,q_0}(t) - \tau_{p,q}(t)), 1), \quad (3.17)$$

where $\text{mod}(\mu, \eta)$ is the remainder of the division of μ by η . $\tau_{p_0,q_0}(t)$ is the delay spread through the RIS reference element. There is no need to consider $\psi_{p,q}(t) \leq 2\pi$ as it is already satisfied in my closed-form solution.

Proof The Pareto optimal solution can be attained based on lemma 3.1 and 3.2.

Lemma 3.1. As the Doppler spread, $B_{\text{Do}}(t)$ in (3.12), is a function of RIS phase shifts, using the following criterion in RIS phase shift design, this effect becomes zero.

$$\frac{d}{dt} \psi_{\tilde{p},\tilde{q}}(t) = \frac{d}{dt} \psi_{p_0,q_0}(t) + 2\pi f_c \frac{d}{dt} \varpi_{\tilde{p},\tilde{q}}(t), \quad (3.18)$$

where $\varpi_{\tilde{p},\tilde{q}}(t) = \tau_{p_0,q_0}(t) - \tau_{\tilde{p},\tilde{q}}(t)$. For brevity, RIS elements except the reference element are shown as $(\tilde{p}, \tilde{q})$.

Proof The Doppler spread can be represented as

$$B_{\text{Do}}(t) = \max\{B_{\text{Do},1}(t), B_{\text{Do},2}(t)\}, \quad (3.19)$$

where the Doppler spread between the reference path and other cascade paths is

$$B_{\text{Do},1}(t) = f_c \max_{\tilde{p}, \tilde{q}} \left| \frac{d}{dt}(\tau_{\tilde{p}, \tilde{q}}(t) + \frac{\psi_{\tilde{p}, \tilde{q}}(t)}{2\pi f_c}) - \frac{d}{dt}(\tau_{p_0, q_0}(t) + \frac{\psi_{p_0, q_0}(t)}{2\pi f_c}) \right|, \quad (3.20)$$

and the Doppler spread between the cascade paths except reference path is

$$B_{\text{Do},2}(t) = f_c \max_{\tilde{p}, \tilde{q}, \tilde{p}', \tilde{q}'} \left| \frac{d}{dt}(\tau_{\tilde{p}, \tilde{q}}(t) + \frac{\psi_{\tilde{p}, \tilde{q}}(t)}{2\pi f_c}) - \frac{d}{dt}(\tau_{\tilde{p}', \tilde{q}'}(t) + \frac{\psi_{\tilde{p}', \tilde{q}'}(t)}{2\pi f_c}) \right|. \quad (3.21)$$

In order to make the Doppler spread zero, We force both $B_{\text{Do},1}$ and $B_{\text{Do},2}$ to zero, which leads to (3.18).

Lemma 3.2. The Pareto optimal solution, (3.17), optimizes (3.11) and (3.12) simultaneously, and after that minimizes $T_{\text{De}}^{\text{upp}}(t)$.

Proof After forcing Doppler spread to zero, We have a feasible set for $\psi_{p,q}(t)$ based on (3.18). First, We integrate (3.18) with respect to t and substitute the result into (3.11). In the next step, in order to maximize the instantaneous cascade channel gain, all the terms of (3.11) should have the same phase. Therefore, $\forall p, q$ choosing

$$\psi_{p,q}(t) = \begin{cases} \psi_{p_0, q_0}(t) & p = p_0, q = q_0, \\ 2\pi f_c \varpi_{\tilde{p}, \tilde{q}}(t) + 2\pi \zeta_{\tilde{p}, \tilde{q}}(t) + \psi_{p_0, q_0}(t) & \text{Otherwise,} \end{cases} \quad (3.22)$$

and $\zeta_{\tilde{p}, \tilde{q}}(t) \in \mathbb{Z}$, maximize (3.11). It is clear that (3.11) is the most important metric among the objective functions, which leads to maximizing signal-to-noise ratio. From (3.18) and (3.22), We see that (3.11) and (3.12) can be simultaneously optimized, irrespective of the phase shift $\psi_{p_0, q_0}(t)$. Due to the causality requirement, $\psi_{p,q}(t) \geq 0$, We can attain the upper bound of delay spread based on (3.13) as

$$T_{\text{De}}^{\text{upp}}(t) = \max_{p,q} \left\{ \tau_{p,q}(t) + \frac{\psi_{p,q}(t)}{2\pi f_c} \right\} - \min_{p,q} \{ \tau_{p,q}(t) \}. \quad (3.23)$$

From (3.22) and (3.23), it is obvious that there is no single solution for optimizing OP₁ and OP₂ simultaneously. As (3.23) is an increasing function in $\psi_{p,q}(t)$, zero phase shift is needed $\forall p, q, t$ to minimize (3.23), which is impossible according to (3.22). Instead, there are infinite non-inferior solutions, [82]. By substituting (3.22) into (3.23), the delay spread upper bound can be obtained based on the possible solutions of OP₁ as

$$T_{\text{De}}^{\text{upp}}(t) = \max \left\{ \tau_{p_0, q_0}(t) + \frac{\psi_{p_0, q_0}(t)}{2\pi f_c}, \max_{\tilde{p}, \tilde{q}} \left\{ \tau_{p_0, q_0}(t) + \frac{\zeta_{\tilde{p}, \tilde{q}}(t)}{f_c} + \frac{\psi_{p_0, q_0}(t)}{2\pi f_c} \right\} \right\} - \min_{p,q} \{ \tau_{p,q}(t) \}. \quad (3.24)$$

In the following, We minimize the objective function in OP₂. Based on (3.22) and the causality requirement, $\psi_{p,q}(t) \geq 0$, We have

$$\zeta_{\tilde{p},\tilde{q}}(t) \geq -f_c \varpi_{\tilde{p},\tilde{q}}(t) - \frac{\psi_{p_0,q_0}(t)}{2\pi}, \quad (3.25)$$

from (3.25) and since $\zeta_{\tilde{p},\tilde{q}}(t) \in \mathbb{Z}$, the minimum value of $\zeta_{\tilde{p},\tilde{q}}(t)$ can be obtained as

$$\zeta_{\tilde{p},\tilde{q}}^{\min}(t) = \left\lceil -f_c \varpi_{\tilde{p},\tilde{q}}(t) - \frac{\psi_{p_0,q_0}(t)}{2\pi} \right\rceil, \quad (3.26)$$

which is a decreasing function with respect to $\psi_{p_0,q_0}(t)$. Equation (3.24) includes additional increasing function, i.e., $\frac{\psi_{p_0,q_0}(t)}{2\pi f_c}$. By substituting $\zeta_{\tilde{p},\tilde{q}}^{\min}(t)$ into (3.24), it is obvious that the variation of $\psi_{p_0,q_0}(t) \in [0, 2\pi]$ results in a small variation, less than $\frac{1}{f_c}$, in $T_{\text{De}}^{\text{upp}}(t)$. Hence, We relax $\zeta_{\tilde{p},\tilde{q}}^{\min}(t)$ to $\zeta_{\tilde{p},\tilde{q}}^{\text{R}}(t) = \lceil -f_c \varpi_{\tilde{p},\tilde{q}}(t) \rceil$, which turns (3.24) into an increasing function with respect to $\psi_{p_0,q_0}(t)$. Accordingly, the closed-form solution for the RIS phase shifts are obtained as (3.17) by considering $\psi_{p_0,q_0}(t) = 0$ and substituting $\zeta_{\tilde{p},\tilde{q}}^{\text{R}}(t)$ into (3.22). This closed-form solution is Pareto optimal based on Th. 4.2.1 in [78]. Accordingly, (3.17) jointly optimizes (3.11) and (3.12), as the first priority order, and minimizes (3.23) as the second priority order. Another potential solution of OP is to reverse the priority order between OP₁ and OP₂. This reversed priority approach leads to non-efficient solution that is presented later in Section 3.5.

Corollary 3.1. With this Pareto optimal solution, the Doppler spread is zero, the maximum value for the instantaneous cascade channel gain is achieved as

$$\frac{P_{\text{R}}^{\max}(t)}{P_{\text{T}}} = \left| \sum_{p=1}^P \sum_{q=1}^Q \Gamma_{p,q}(t) \right|^2, \quad (3.27)$$

and the delay spread upper bound is

$$T_{\text{De}}^{\text{upp},\min}(t) = \max\{\tau_{p_0,q_0}(t), \max_{\tilde{p},\tilde{q}}\{\tau_{p_0,q_0}(t) + \frac{\zeta_{\tilde{p},\tilde{q}}^{\text{R}}(t)}{f_c}\}\} - \min_{p,q}\{\tau_{p,q}(t)\}. \quad (3.28)$$

As can be seen in Fig. 3.3, all the circular paths of the RIS elements have the same center located exactly between the Tx and Rx. With this symmetrical feature, the proposed closed-form solution works for all time slots due to the periodicity of the mobility patterns of the RIS elements. We obtain the closed-form solution for the time-varying RIS phase shifts based on the achieved geometric channel model. This only depends on the locations of Tx and Rx, and the known time-varying position of the aerodynamic HAPS based on its predictable mobility. In this work, We assume the locations to be known to the HAPS which can be obtained before the flight or during the flight for instance, based on the GPS signals to find the location of the HAPS or beacon signals sent by ground stations. Therefore, my solution is practical

while being simple to implement, as the RIS phase shifts can be efficiently calculated on the HAPS side based on the location information.

3.5 Numerical Evaluations of The Proposed RIS Phase Shift Design

In this section, We evaluate the performance of my proposed RIS phase shift design in Section 3.4. We assume a circular path with the origin $(0, 0, 0)$ and the radius $R_0 = 3$ km parallel to xy -plane. The RIS dimensions are chosen in a way such that $a = 20 \times b$, i.e., the length is much larger than the width. This is because the RIS is mounted below the HAPS wing, as in Fig. 3.2. The RIS element dimensions are chosen as

$$d_x = d_y = \frac{\lambda_c}{5}, \quad (3.29)$$

where $f_c = 2$ GHz, and hence, the total number of RIS elements can be obtained as

$$P \times Q = \lceil \frac{a}{d_x} \rceil \times \lceil \frac{b}{d_y} \rceil = \lceil \frac{5a}{\lambda_c} \rceil \times \lceil \frac{a}{4\lambda_c} \rceil. \quad (3.30)$$

HAPS altitude and velocity of 20 km and $v = 110$ km/h are used in my simulations, respectively. These parameters are inline with the specifications of one of the well-known aerodynamic HAPS, HAWK30, [27, 49]. The terrestrial Tx and Rx coordinates in the scale of km are $(x_T, y_T, z_T) = (-5, 0, 20)$ and $(x_R, y_R, z_R) = (5, 0, 20)$, respectively. The planar antenna gain of RIS element (p, q) to S can be considered as

$$g_{p,q}^S(\theta_{p,q}^S(t), \varphi_{p,q}^S(t)) = \frac{4\pi}{\lambda_c^2} d_x d_y \cos \theta_{p,q}^S(t), \quad (3.31)$$

for $\theta_{p,q}^S(t) \in [0, \frac{\pi}{2}]$ and zero otherwise, [81]. The gains of the transmit and receive antennas are $g_S^{p,q}(t) = 1$. As mentioned in *Lemma 3.2*, an alternative approach to my proposed method is optimization with reversed priority, i.e., reversing the order of OP_1 and OP_2 in the optimization process. Hence, in the following, We compare my proposed method with this alternative approach.

In Fig. 3.5 and Fig. 3.6, the cascade channel gain and $T_{De}^{upp}(t)$ of the proposed method and reversed approach are compared at a snapshot $t_0 = 10$ s. Using the result of *Corollary 3.1*, in Fig. 3.5, We plot the cascade channel gain versus RIS dimensions. As can be seen, in Fig. 3.5, the reversed approach leads to a poor performance compared to my proposed method. Exploiting the proposed method

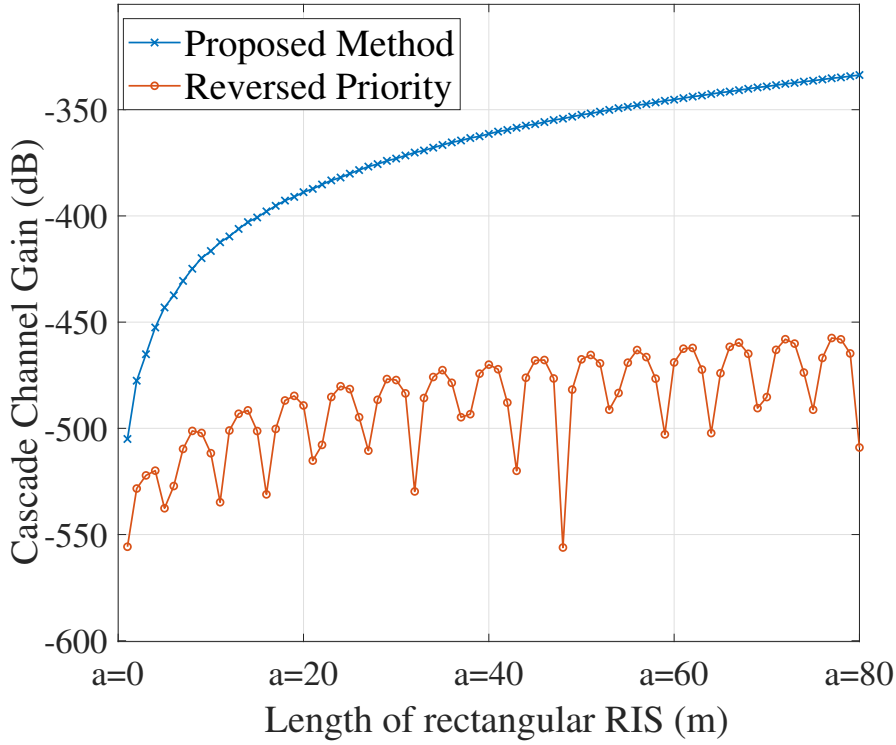


Fig. 3.5 Cascade channel gain versus RIS dimensions at $t = t_0$.

makes the cascade channel gain controllable and it can be constructively increased by increasing the RIS dimensions. In contrast, the cascade channel gain based on reversed approach is uncontrollable as the only controllable parameter, i.e., the RIS phase shifts are fixed. This is due to the fact, mentioning in *Lemma 3.2*, that $\psi_{p,q}(t)$ is considered zero $\forall p, q, t$ to optimize $T_{\text{De}}^{\text{upp}}(t)$ with the first priority order. By substituting $t = t_0$ s and zero phase shifts in (3.11), the cascade channel gain can be formulated as

$$\frac{P_{\text{R}}(t_0)}{P_{\text{T}}} = \left| \sum_{p=1}^P \sum_{q=1}^Q \Gamma_{p,q}(t_0) \exp(-j2\pi f_c \tau_{p,q}(t_0)) \right|^2. \quad (3.32)$$

The term $\exp(-j2\pi f_c \tau_{p,q}(t_0))$ can negatively affect the cascade channel gain and makes it uncontrollable. Adopting the results of *Corollary 3.1*, in Fig. 3.6, We plot $T_{\text{De}}^{\text{upp}}(t_0)$ versus RIS dimensions to compare the proposed method and the reversed one. It can be seen that the delay spread gap between my proposed method and the reversed priority is negligible. Furthermore, by extrapolating Fig. 3.6, We can see that for $a = 80$ m, $T_{\text{De}}^{\text{upp}}(t_0)$ is around 8×10^{-8} s. This is due to the almost linear behavior of $T_{\text{De}}^{\text{upp}}(t_0)$ as a function of a . Therefore, (3.17) can keep the delay spread upper bound controllable even for a large number of RIS elements. The claims for

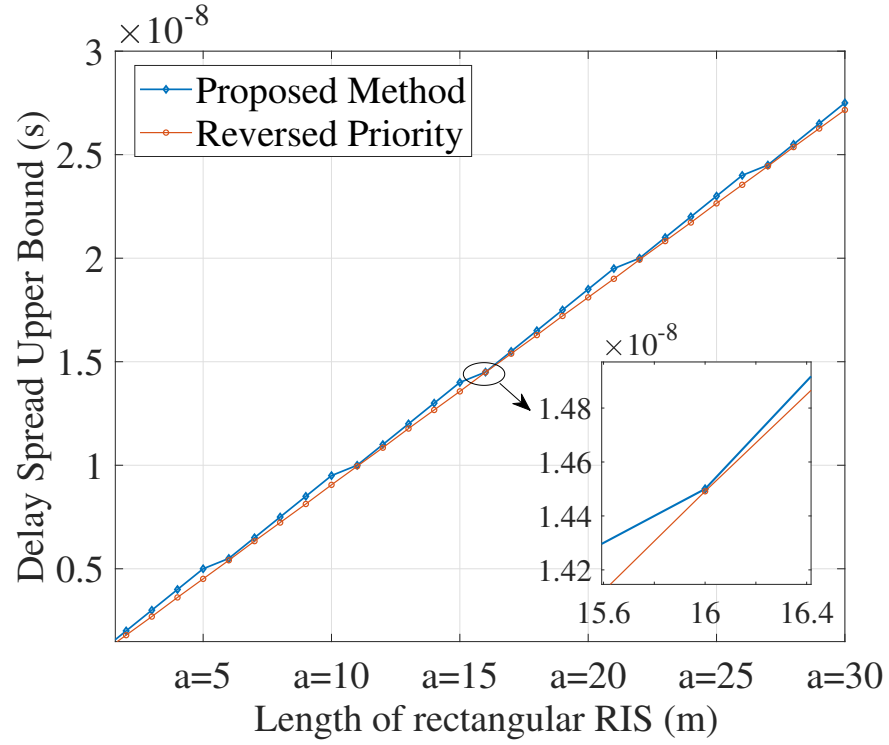


Fig. 3.6 Delay spread upper bound versus RIS dimensions at $t = t_0$.

Fig. 3.5 and Fig. 3.6 are feasible for any $t = t_0$ based on the results presented in Figs. 3.7 and 3.8. In Figs. 3.7 and 3.8, We analyze the cascade channel gain and $T_{\text{De}}^{\text{upp}}(t)$ versus time for different RIS dimensions, respectively. Fig. 3.7 shows that by increasing the value of a from 10 m to 20 m, the cascade channel gain can be increased by 27.7 dB. As can be seen, the fluctuation is less than 0.1 dB and can be ignored as it is negligible compared to the average value of the cascade channel gain. There is no significant benefit to consider the time-varying transmit signal to compensate this negligible fluctuation. In Fig. 3.8, We plot $T_{\text{De}}^{\text{upp}}(t)$ versus time to compare my proposed method with the reversed approach. As can be seen, the gap is less than 5×10^{-10} s and it is negligible. In addition, it is clear that (3.17) can make $T_{\text{De}}^{\text{upp}}(t)$ controllable for different time slots.

Adopting numerical methods such as exhaustive search is intractable in terms of computational complexity in my proposed high-mobility scenario. This is because such a search method must be done for massive number of RIS elements with time-varying phase shifts, which needs huge computational complexity for each short time slot. Let us elaborate more on this with the following explanation. Even if We relax the continuous RIS phase shifts to discrete ones with M quantization levels, to simplify the problem, the search space has M^{PQ} states. The number of RIS elements can be

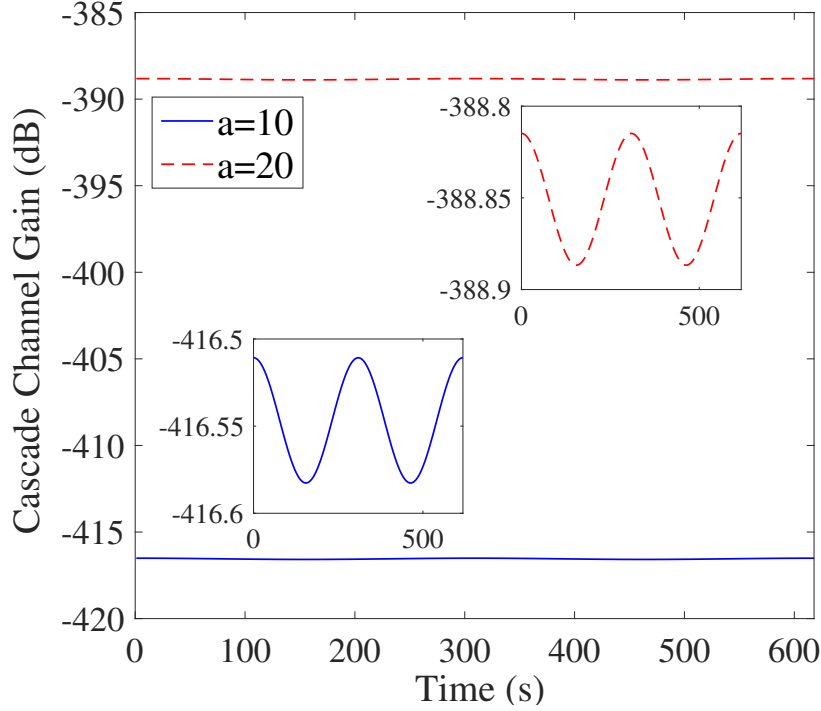


Fig. 3.7 Cascade channel gain versus time for different RIS dimensions.

obtained as $P \times Q = \lceil \frac{a}{d_x} \rceil \times \lceil \frac{b}{d_y} \rceil = \lceil \frac{5a}{\lambda_c} \rceil \times \lceil \frac{a}{4\lambda_c} \rceil$ as We consider $a = 20 \times b$ where a and b are the RIS dimensions. Furthermore, the dimensions of RIS elements can be obtained as $d_x = d_y = \frac{\lambda_c}{5}$ where $f_c = 2$ GHz. For more simplification, even if We consider $M = 2$ and use 0.01 of the HAPS wing area to mount RIS, We have $P \times Q = \lceil \frac{a}{d_x} \rceil \times \lceil \frac{b}{d_y} \rceil = \lceil \frac{8}{0.03} \rceil \times \lceil \frac{\frac{8}{20}}{0.03} \rceil = 3738$. Hence, even in this case, We have $2^{3738} \simeq 2^{3740} = (2^{10})^{374} \simeq (10^3)^{374} = 10^{1122}$ states to be searched in a very short time slot. As this is a massive number, finding the optimal solution in numerical approach is intractable in terms of computational complexity.

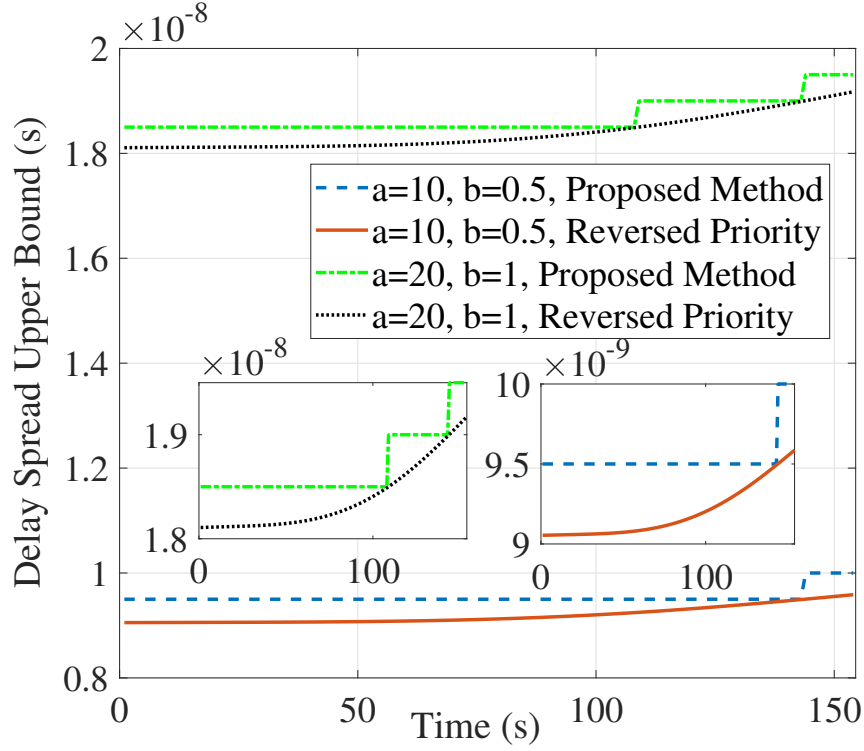


Fig. 3.8 Delay spread upper bound versus time for different RIS dimensions.

3.6 Lessons Learned and Conclusion

In this chapter, We answered the first research question of this thesis by demonstrating that an aerodynamic HAPS-mounted RIS can reliably connect unconnected ground stations despite time-varying channel effects. By exploiting the predictable mobility of the aerodynamic HAPS, channel time variation was transformed from a fundamental obstacle into a controllable design parameter. A multi-objective optimization framework was formulated to jointly maximize the cascade channel gain, eliminate Doppler spread, and minimize the delay spread upper bound. By adopting Pareto optimality and introducing a reference RIS element, a closed-form solution for the RIS phase shifts was derived. This solution achieves gain maximization and zero Doppler spread while keeping the delay spread controllable, without requiring continuous channel tracking or repeated high-complexity optimization. The results presented in this chapter demonstrate that incorporating platform mobility into the system design provides an effective approach for improving communication reliability in highly dynamic environments. Rather than treating mobility as an impairment to be mitigated, the proposed framework exploits its predictable behaviour to enable an analytical and computationally efficient design. Moreover, the proposed framework

maintains scalable computational complexity as the RIS size increases, making it suitable for large-scale RIS deployments.

While this chapter confirms that a single aerodynamic HAPS-RIS can restore connectivity in blockage scenarios, practical wireless systems must address scalability, heterogeneity, and infrastructure limitations. This naturally motivates the transition to multi-tier architectures. In the next chapter, the focus shifts from single-platform connectivity to the integration of HAPS-RIS with UAV-based networks. Thus, the thesis progresses from mobility-aware link-level design toward system-level architectural optimization of non-terrestrial networks.

Chapter 4

Exploring the Impact of Aerostatic HAPS–RIS on UAV-based Networks: A Hierarchical Framework

This chapter initiates the second technical contribution of the PhD thesis and transforms the conceptual gaps identified in chapter 2 into a concrete architectural investigation. Chapter 3 demonstrated that even under high mobility, aerodynamic HAPS-RIS can control time-varying channel effects and restore connectivity at the link level. While aerodynamic HAPS offers low-cost and swift deployment, aerostatic HAPS provides significantly longer endurance and substantially higher payload capacity [27]. These properties enable aerostatic HAPS-RIS to act as persistent auxiliary infrastructure layer capable of supporting other non-terrestrial systems. While there has been considerable progress in exploiting aerostatic HAPS-RIS to improve wireless networks, a critical gap remains in applying this technology to UAV-assisted networks. To the best of my knowledge, based on the literature surveyed in this thesis, no prior work has investigated the integration of aerostatic HAPS-RIS technology with UAV-assisted networks in which UAVs operate as aerial base stations. Consequently, the main research question that arises is “*How can wireless network architectures be redesigned through aerostatic HAPS-RIS and UAV platforms to maximize service coverage while reducing UAV deployment requirements?* ” which is fully addressed in this chapter. The motivations, challenges, and contributions of this chapter are shown at a glance in Fig. 4.1. This technical contribution is published in IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), 2025.

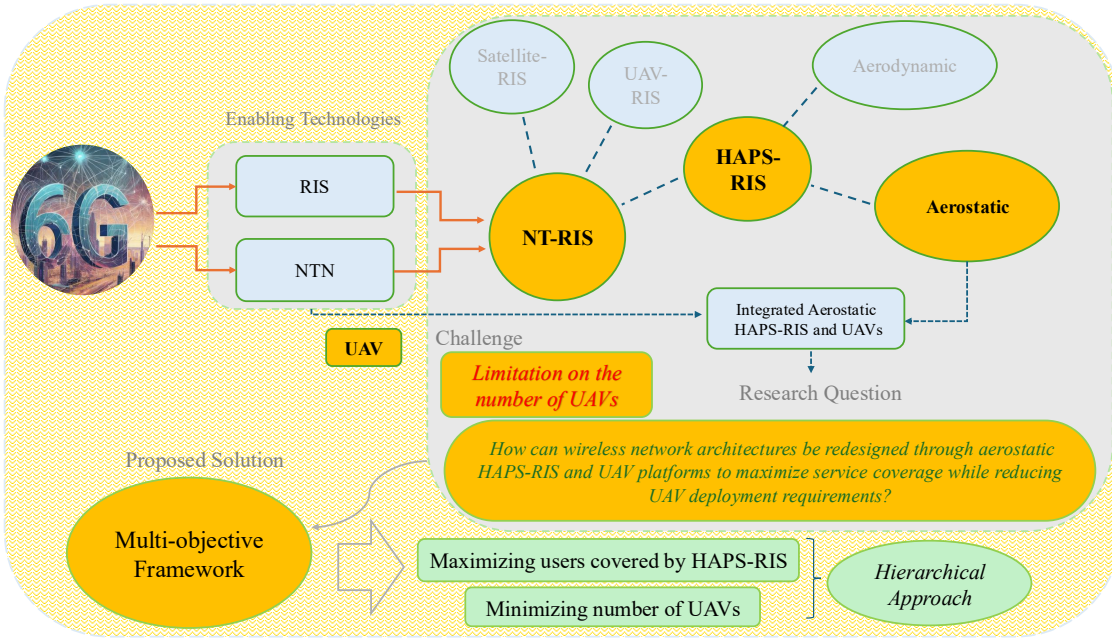


Fig. 4.1 Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.

4.1 The Main Contributions of this Chapter

The main contributions of this technical chapter can be summarized as:

- We introduce a *novel network architecture* where a supportive network exploiting HAPS-RIS is established to address a key challenge in UAV-based networks, reducing the number of required UAVs.
- We mathematically model the heterogeneous zones, i.e., UAV zone and HAPS-RIS zone for user clustering and associate zone users with their allocated infrastructure, i.e., UAV or HAPS-RIS.
- We propose a novel hierarchical bilevel optimization problem, including a leader and a follower problem. In the leader one, We obtain the zone boundary and a practical design for the RIS phase shifts to maximize the number of users supported by HAPS-RIS while satisfying the rate requirements for each user in the HAPS-RIS zone. We practically relax and redesign the leader problem into an optimization problem with the lower computational complexity, and solve it with the proposed DyRaZARC technique. In the follower optimization problem, We aim to minimize the number of UAVs while meeting the rate

requirement for each user in the UAV zone. To solve the follower problem, We propose a novel geometry-informed machine learning method, called KADUS technique. My findings demonstrate that enhancing the number of RIS elements can significantly reduce the required number of UAVs, revealing a key strategy for optimizing aerial operations.

4.2 Proposed Network Architecture

We consider a downlink transmission scenario, shown in Fig. 5.3, where heterogeneous non-terrestrial infrastructures are exploited to bring connectivity to a remote area. The set of stationary users $\mathcal{I}$ is defined as $\mathcal{I}=\{1, \dots, I\}$, where $i \in \mathcal{I}$ represents an individual user indexed by i . The users are uniformly distributed in a circular area where there is no nearby terrestrial infrastructure. The angular coordinate is obtained as

$$\theta \sim \mathcal{U}(0, 2\pi), \quad (4.1)$$

where $\mathcal{U}(a, b)$ is a uniformly random distribution over the interval $[a, b]$. While the radial coordinate is obtained as

$$r = R\sqrt{u}, \quad (4.2)$$

where $u \sim \mathcal{U}(0, 1)$ and R denotes the radius of the area. The user coordinates are then computed as

$$x = r \cos(\theta), \quad y = r \sin(\theta). \quad (4.3)$$

Uniform spatial user distribution is a commonly adopted model for performance evaluation in wireless communication systems. Other user distribution models, including stochastic geometry based on Poisson point processes (PPPs), have also been widely studied for modelling wireless communication networks [83]. The set of UAVs $\mathcal{J}$ is defined as $\mathcal{J} = \{1, \dots, J\}$, where $j \in \mathcal{J}$ represents an individual UAV indexed by j . In this scenario, the UAVs remain stationary, hovering in place to provide service to the fixed users. The aim is minimizing the number of required UAVs with exploiting terrestrial CS and HAPS-RIS while providing full coverage with meeting the minimum rate requirements. In HAPS-RIS scenarios, CS uses high gain directional antenna, creating a dominated line of sight (LoS) connection with HAPS [28, 29, 64–66]. We consider UAVs and CS operate independently to provide connectivity and they are not connected to each other. All UAVs can be connected to the core network via a backhaul link. Due to heavy blockage, there is no direct link between the users and the

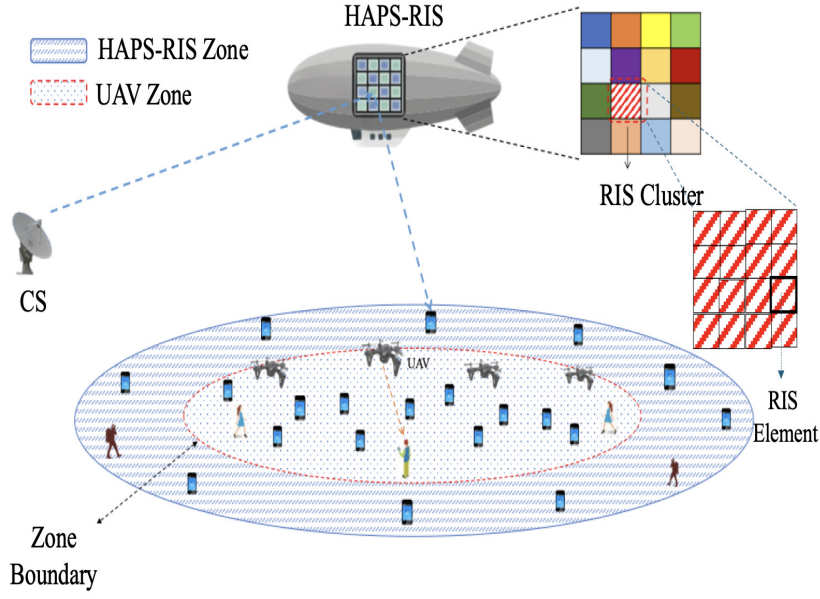


Fig. 4.2 The Proposed Network Architecture

CS; communication instead occurs through a cascaded channel through HAPS-RIS. The set of RIS elements $\mathcal{M}$ is defined as $\mathcal{M} = \{1, \dots, M\}$, where $m \in \mathcal{M}$ represents the RIS element indexed by m . Users can be connected to the network either through the UAV system or the HAPS-RIS setup, but not through both at the same time. The coverage area is a circle with the radius R_0 with the centre of (x_0, y_0, z_0) , the CS location is $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}})$, the location of the HAPS is $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}})$, and the location of the UAV j is $(x_j^{\text{UAV}}, y_j^{\text{UAV}}, z_j^{\text{UAV}})$ in the Cartesian coordinate system. As can be seen in Fig. 5.3, there are two zones in the coverage area, i.e., the inner circle with the radius R and the ring around it. The *UAV zone* is the area where the users are covered by UAVs and the *HAPS-RIS zone* is the ring area between the inner and outer circles, in which the users are covered by HAPS-RIS. The border which separates the UAV zone and the HAPS-RIS zone is called *zone boundary*. $\mathcal{B}$ is the set which includes the users in the UAV zone. Thus, $\mathcal{C} = \mathcal{I} - \mathcal{B}$ is the set which includes users in the HAPS-RIS zone. The set of equally spaced orthogonal subcarriers L is defined as $L = \{1, \dots, L^{\text{tot}}\}$, where $l \in L$ represents the subcarrier indexed by l . Let us consider the available bandwidth of BW which is divided into L^{tot} . Therefore, the bandwidth allocated to each orthogonal subcarrier is $B_l = \frac{BW}{L^{\text{tot}}}$.

4.3 Problem Formulation and Proposed Solution Techniques

We propose a hierarchical bilevel optimization problem, including the leader problem **OP 1** and the follower problem **OP 2**. In **OP 1**, We determine the zone boundary in order to maximize the number of users in the HAPS-RIS zone while satisfying the rate requirement for each user. We consider **OP 1** as the leader problem, because the aim is to fully utilize the resources of HAPS-RIS system to assist the UAV-based network by maximizing the number of users in the HAPS-RIS zone. Accordingly, the number of users in the UAV zone is minimized, and hence, less number of UAVs is required. After solving **OP 1**, in the follower problem **OP 2**, We obtain the minimum number of UAVs subject to the user rate requirements for the users in the UAV zone.

4.3.1 Proposed HAPS-RIS Zone Design

In the HAPS-RIS zone, h_{im}^{CS} is the cascade channel gain between user i -RIS and RIS-CS through RIS element m .

$$h_{im}^{\text{CS}} = \sqrt{G^{\text{CS}} G_i (\mathcal{L}_m^{\text{CS-RIS}})^{-1} (\mathcal{L}_{im}^{\text{RIS-user}})^{-1}}, \forall m, \forall i \in \mathcal{C}, \quad (4.4)$$

where G^{CS} is the antenna gain of the CS and G_i is the antenna gain of the user i . $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}})$, (x_i, y_i, z_i) , $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}})$, $(x_m^{\text{RIS}}, y_m^{\text{RIS}}, z_m^{\text{RIS}})$ are the CS, user i , HAPS, and RIS element m , coordinates, respectively. Using the Friis model, [41], the path loss between CS and RIS element m , $\forall m$, can be formulated as

$$\mathcal{L}_m^{\text{CS,RIS}} = \left(\frac{4\pi f_c}{c}\right)^2 \times ((x_m^{\text{RIS}} - x^{\text{CS}})^2 + (y_m^{\text{RIS}} - y^{\text{CS}})^2 + (z_m^{\text{RIS}} - z^{\text{CS}})^2), \quad (4.5)$$

and the path loss between RIS element m and the user i , $\forall m, \forall i \in \mathcal{C}$, can be formulated as

$$\mathcal{L}_{im}^{\text{RIS,user}} = \left(\frac{4\pi f_c}{c}\right)^2 \times ((x_m^{\text{RIS}} - x_i)^2 + (y_m^{\text{RIS}} - y_i)^2 + (z_m^{\text{RIS}} - z_i)^2), \quad (4.6)$$

where f_c is the carrier frequency and c is the speed of wave propagation which is considered to be equal to the speed of light. The communication rate of the user i

received from the CS through the HAPS-RIS can be obtained as

$$r_i^{\text{CS}} = \sum_{l=1}^{L^{\text{CS}}} B_l \log_2 \left(1 + \gamma_i^{l,\text{CS}} \right), \forall i \in \mathcal{C}, \quad (4.7)$$

where $L^{\text{CS}} = \frac{L^{\text{tot}}}{2}$ is available subcarriers, $\gamma_i^{l,\text{CS}}$, the signal to noise ratio (SNR) of the received signal at user i and subcarrier l , can be obtained as

$$\gamma_i^{l,\text{CS}} = \frac{P^{l,\text{CS}} \left| \sum_{m=1}^M \rho_{im}^{l,\text{CS}} h_{im}^{\text{CS}} \vartheta_{im} \right|^2}{N_0 B_l}, \forall i \in \mathcal{C}, \forall l, \quad (4.8)$$

where M is the total number of RIS elements, N_0 is the noise power spectral density, and $P^{l,\text{CS}}$ is the CS transmit power allocated uniformly to the subcarrier l . $\rho_{im}^{l,\text{CS}}$ is the binary variable which demonstrates the user i is assigned to RIS element m over subcarrier l .

Considering ϑ_{im} the reflection coefficient of the RIS element m corresponding to the user i as

$$\vartheta_{im} = \mu_m e^{-j(\phi_m - \xi_m^{\text{CS}} - \omega_{im})}, \forall i \in \mathcal{C}, m, \quad (4.9)$$

where ϕ_m is the RIS phase shift for the element m . ξ_m^{CS} is the corresponding phase between RIS element m and the CS. ω_{im} is the corresponding phase between RIS element m and the user i . μ_m is the reflection loss corresponding to the RIS element m .

Remark 4.1: Users in the HAPS-RIS zone are assumed to be orthogonal to each other and to the users of the UAV zone. Hence, there is no inter-user interference.

Definition 4.1: Similar to the approach in [66], where the justification is elaborated in detail, We consider each user in the HAPS-RIS zone is allocated to its own group of subcarriers and RIS elements. The group of RIS elements which are allocated to a user is called *RIS cluster*. Given this assumption, $\rho_{im}^{l,\text{CS}}$ can be obtained based on the value of R , the radius of the inner circle, which determines the zone boundary, elaborated in the proposed DyRaZARC Technique. Taking all these factors into account, the leader optimization problem can be formulated as

$$\text{OP 1 : } \max_{R, \vartheta_{im}} U^{\text{HAPS}} \quad (4.10a)$$

$$\text{s.t. : } r_i^{\text{CS}}(R, \vartheta_{im}) \geq r_0^{\text{user}}, \forall i \in \mathcal{C}, \quad (4.10b)$$

where U^{HAPS} is the number of users covered by HAPS-RIS in the HAPS-RIS zone and r_0^{user} is the minimum rate requirement for each user.

Proposition 4.1: **OP 1** can be relaxed into

$$\textbf{OP 1-a : } \max_R U^{\text{HAPS}} \quad (4.11a)$$

$$\text{s.t. : } r_i^{\text{CS}}(R) \geq r_0^{\text{user}}, \forall i \in \mathcal{C}, \quad (4.11b)$$

where $\phi_m^* = \xi_0 + \omega_0 + 2k\pi$, $\forall m$ and k can be an integer value.

Proof In the proposed geometrical case, the dimensions of RIS can be negligible compared to the altitude of HAPS, as it does not have much effect on the performance. Hence, without loss of generality, We relax the location of the RIS elements as

$$(x_m^{\text{RIS}}, y_m^{\text{RIS}}, z_m^{\text{RIS}}) \approx (x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}}), \quad \forall m, \quad (4.12)$$

the dimensions of the RIS and the coverage area is much less than the range of the distance between HAPS-RIS and the terrestrial components.¹ Accordingly, without loss of generality, I can relax the corresponding phases to fixed values as $\xi_m^{\text{CS}} \approx \xi_0, \forall m$ and $\omega_{im} \approx \omega_0, \forall i \in \mathcal{C}, \forall m$, so the reflection gain of RIS element m can be relaxed as $\vartheta_{im} \approx \tilde{\vartheta}_m, \forall i \in \mathcal{C}, \forall m$ where

$$\tilde{\vartheta}_m = \mu_m e^{-j(\phi_m - \xi_0 - \omega_0)} \quad \forall m. \quad (4.13)$$

As (5.18) is independent from user index, $r_i^{\text{CS}}(R, \tilde{\vartheta}_m)$ can be relaxed to its upper bound by considering $\phi_m^* = \arg \max_{\phi_m} \tilde{\vartheta}_m = \xi_0 + \omega_0 + 2k\pi, \forall m$. Accordingly, (4.10b) is relaxed into (5.12b) and hence **OP 1** is relaxed into **OP 1-a**. The proposed technique significantly reduces the computational complexity by eliminating the need to individually optimize the phase shifts for each RIS element. Given a massive number of RIS elements in HAPS-RIS scenarios, ranging from 10^5 to 10^8 , see Section. 4.4, the proposed design can pave the way for scalability and enables practical implementation.

Proposition 4.2: **OP 1-a** can be transformed as

$$\textbf{OP 1-b : } \min_R R^2 \quad (4.14a)$$

¹The dimensions of the RIS are in the range of 100 meters while the distance between the HAPS-RIS and the terrestrial network is in the range of more than 20 kilometers.

The Proposed DyRaZARC Technique: 1 Solving OP 1-b to Obtain the Zone Boundary

s1: Initialize $t = 0$, $\delta = 50$, $R^* = R_0$, and define the set $\mathcal{I} = \{i | \sqrt{x_i^2 + y_i^2} \leq R_0\}$

s2: **for** $t = 1$ to T **do**

s3: Define the set $\mathcal{B}^{(t)} = \{i' | \sqrt{x_{i'}^2 + y_{i'}^2} \leq R^{(t)}\}$ where $R^{(t)} = R_0 - t\delta$. T is the upper limit of the iteration count.

s4: Define the set $\mathcal{C}^{(t)} = \mathcal{I} - \mathcal{B}^{(t)}$ where the users in this area are supported by HAPS-RIS, and then calculate the number of the RIS elements per each cluster as $\left\lfloor \frac{M}{|\mathcal{C}^{(t)}|} \right\rfloor$.

s5: Map $|\mathcal{C}^{(t)}|$ clusters of RIS elements to $|\mathcal{C}^{(t)}|$ users based on a random injective function. Allocate $L_{\text{cluster}}^{(t)} = \lfloor \frac{L^{\text{CS}}}{|\mathcal{C}^{(t)}|} \rfloor$ subcarriers to each RIS cluster. Then, uniformly allocate $L_{\text{cluster}}^{(t)}$ subcarriers to $\left\lfloor \frac{M}{|\mathcal{C}^{(t)}|} \right\rfloor$ RIS elements for each RIS cluster and calculate $\rho(R^{(t)})$.

s6: **While** $r_i^{\text{CS}}(\rho(R^{(t)})) \geq r_0^{\text{user}}, \forall i \in \mathcal{C}$ or $t < T$, set $R^* = R^{(t)}$.

s7: Set $t = t + 1$

s8: **end for**

s9: R^* is the final solution of **OP 1-b**.

$$\text{s.t. : } r_i^{\text{CS}}(R) \geq r_0^{\text{user}}, \forall i \in \mathcal{C}, \quad (4.14b)$$

Proof Maximizing U^{HAPS} is equivalent to maximizing the area of HAPS-RIS zone which is $\pi(R_0^2 - R^2)$. R_0 is the outer circle radius and as it has a fixed value, maximizing $\pi(R_0^2 - R^2)$ is equivalent to minimizing πR^2 .

The solution of **OP 1-b**, i.e., R^* , is obtained by the proposed DyRaZARC technique. In each iteration, the zone boundary and user sets are updated, and users in the HAPS-RIS zone are assigned to their respective RIS clusters using a random injective function, with an equal number of subcarriers allocated to each user. In the proposed geometric channel model for the HAPS-RIS zone, the channel gain is affected by the locations of the RIS clusters, the users, and the CS. Hence, the random allocation of RIS clusters is justified due to the geometric configuration of the system, where the RIS dimensions are negligible compared to the distances between the HAPS and the users. Furthermore, an injective function is adopted to ensure that each user in the HAPS-RIS zone is uniquely assigned to one of the available RIS clusters. This process continues until the maximum number of users in the HAPS-RIS zone is achieved while satisfying the rate requirement.

4.3.2 Proposed UAV Zone Design

In the UAV zone, the communication rate of the user i can be obtained as

$$r_i^{\text{UAV}} = \sum_{j=1}^{N^{\text{UAV}}} \sum_{l'=1}^{L^{\text{UAV}}} B_l \log_2 \left(1 + \gamma_{ij}^{l', \text{UAV}} \right), \forall i \in \mathcal{B}, \quad (4.15)$$

where the available subcarriers are $L^{\text{UAV}} = \frac{L^{\text{tot}}}{2}$. Hence, the signal to interference plus noise ratio (SINR) of the user i served by UAV j over subcarrier l' , $\forall i \in \mathcal{B}, \forall j, l'$, can be obtained as

$$\gamma_{ij}^{l', \text{UAV}} = \frac{P_{ij}^{l', \text{UAV}} \rho_{ij}^{l', \text{UAV}} |h_{ij}^{l', \text{UAV}}|^2}{N_0 B_l + \sum_{j' \neq j}^J P_{ij'}^{l', \text{UAV}} \rho_{ij'}^{l', \text{UAV}} |h_{ij'}^{l', \text{UAV}}|^2}, \quad (4.16)$$

where $P_{ij}^{l', \text{UAV}}$ is the transmit power of the UAV j allocated to the subcarrier l' and the user i . $h_{ij}^{l', \text{UAV}}$ is the channel gain between UAV j and user i over subcarrier l' , which can be formulated as $h_{ij}^{\text{UAV}} = \sqrt{G_j^{\text{UAV}} G_i \bar{\mathcal{L}}_{ij}^{-1}}$, $\forall i \in \mathcal{B}, \forall j$. G_j^{UAV} is the antenna gain of the UAV j , G_i is the antenna gain of the user i , and $\bar{\mathcal{L}}_{ij}$ is the average path loss, $\forall i \in \mathcal{B}, \forall j$, which can be obtained as [84]

$$\bar{\mathcal{L}}_{ij} = P_{ij, \text{LoS}}^{\text{UAV}} \eta_1 \left(\frac{4\pi f_c}{c} d_{ij} \right)^\alpha + P_{ij, \text{NLoS}}^{\text{UAV}} \eta_2 \left(\frac{4\pi f_c}{c} d_{ij} \right)^\alpha, \quad (4.17)$$

where α is the path loss exponent, η_1 and η_2 are the excessive path losses corresponding to the LoS and non-LoS connections, respectively. The distance between the user i and the UAV j , $\forall i \in \mathcal{B}, \forall j$, can be formulated as

$$d_{ij} = \sqrt{(x_i - x_j^{\text{UAV}})^2 + (y_i - y_j^{\text{UAV}})^2 + (z_j^{\text{UAV}})^2}, \quad (4.18)$$

and $P_{ij, \text{LoS}}^{\text{UAV}}$ is the LoS probability between the user i and the UAV j as

$$P_{ij, \text{LoS}}^{\text{UAV}} = \frac{1}{1 + \psi e^{-\beta(\tilde{\theta}_{ij} - \psi)}}, \quad (4.19)$$

where β and ψ are the constant values that depend on the environment type. $P_{ij, \text{LoS}}^{\text{UAV}} + P_{ij, \text{NLoS}}^{\text{UAV}} = 1, \forall i \in \mathcal{B}, \forall j$, and $\tilde{\theta}_{ij} = \frac{180}{\pi} \arcsin\left(\frac{z_j^{\text{UAV}}}{d_{ij}}\right), \forall i \in \mathcal{B}, \forall j$.

Remark 4.2: In the UAV zone, Iexploit orthogonal frequency division multiple access (OFDMA), and hence, there are multi UAV cells where there is inter-cell interference but no intra-cell interference.

The Proposed Geometry-informed Machine Learning KADUS Technique:
2 Solving OP 2

s1: Initialize $\delta'=1$, $N^{\text{UAV},(0)}$ and define the set $\mathcal{B}^*=\{i'|\sqrt{x_{i'}^2+y_{i'}^2}\leq R^*\}$ where R^* is the final solution of **OP 1-b**.

s2: **for** $t = 1$ to T **do**

s3: Obtain $\mathbf{x}(N^{\text{UAV},(t)})$, $\mathbf{y}(N^{\text{UAV},(t)})$, and the user association part of $\tilde{\boldsymbol{\rho}}(N^{\text{UAV},(t)})$ based on the k -means clustering method for the users as members of the set $\mathcal{B}^*$, where $N^{\text{UAV},(t)} = N^{\text{UAV},(0)} - (t-1)\delta'$.

s4: Apply orthogonality check for subcarriers based on the constraint $\sum_i^I \tilde{\rho}_{ij}'' \leq 1 \forall i', j$.

Then calculate $\tilde{\boldsymbol{\rho}}(N^{\text{UAV},(t)})$.

s5: **While** $t < T$ or $r_i^{\text{UAV}}(\tilde{\boldsymbol{\rho}}(N^{\text{UAV},(t)}), \mathbf{x}(N^{\text{UAV},(t)}), \mathbf{y}(N^{\text{UAV},(t)})) \geq r_0^{\text{user}}, \forall i \in \mathcal{B}$, set $N^* = N^{\text{UAV},(t)}$.

s6: Set $t = t + 1$

s7: **end for**

s8: N^* is the final solution of **OP 2**.

Definition 4.2: $\tilde{\boldsymbol{\rho}}$ is obtained based on N^{UAV} via k -means clustering and satisfying subcarrier orthogonality in each UAV cluster. Considering all these factors, the follower optimization problem can be designed as

$$\text{OP 2 : } \min_{N^{\text{UAV}}} N^{\text{UAV}} \quad (4.20a)$$

$$\text{s.t. : } r_i^{\text{UAV}}(N^{\text{UAV}}) \geq r_0^{\text{user}}, \forall i \in \mathcal{B}. \quad (4.20b)$$

The solution of **OP 2**, i.e., minimum number of required UAVs, is achieved by exploiting the proposed geometry-informed machine learning KADUS technique, for the given zone boundary which is obtained in **OP 1**. Unlike conventional k -means clustering, where the k -factor is a fixed input [85], the proposed KADUS technique considers it as a varying number of UAVs that adapts iteratively. This approach increases the network degrees of freedom. In each iteration, the users are associated to the UAVs using k -means clustering method while satisfying the subcarrier orthogonality and the rate requirement. The process continues until minimum number of UAVs is obtained.

Corollary 4.1: The solution of the proposed hierarchical bilevel optimization framework including the leader problem, **OP 1** which is defined in *Definition 4.1*, and the follower one, **OP 2** which is defined in *Definition 4.2*, is $(R, \boldsymbol{\vartheta}, N^{\text{UAV}}) = (R^*, \boldsymbol{\vartheta}^*, N^*)$. $\boldsymbol{\vartheta}^*$ can be obtained via *Proposition 4.1* where the RIS phase shifts

are practically designed in **OP 1-a**. With the given ϑ^* , R^* can be obtained via *Proposition 4.2* and the proposed DyRaZARC technique. Then, with the given R^* , N^* can be obtained by the proposed geometry-informed machine learning KADUS technique.

4.3.3 Model Limitations

In the following, we define the scope and limitations of the proposed framework. The backhaul connectivity is not considered, as the focus of this chapter is on the access network and the proposed communication resource allocation framework. Incorporating backhaul-aware optimisation into the proposed architecture represents an important direction for future work. The power consumption of the UAVs is not considered in this chapter, while the total average UAV path loss term and the total power consumption constraint are considered in Chapter 5. While UAV deployment is not obtained through a placement optimization, a more comprehensive approach of the UAV positioning problem is presented in Chapter 5.

4.4 Numerical Evaluations

In the simulation setup, the selected values for the HAPS-RIS system are based on established models and findings in the relevant literature [28, 64], while the values chosen for the UAVs align with the assumptions in [14, 84]. We consider $I = 20$ users which are spread in random locations following the uniform distribution inside a circle area with the center $(x_0, y_0, z_0) = (0, 0, 0)$ and the radius of $R_0 = 500$ meters. The CS is located at $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}}) = (-10000, 0, 1000)$ and the HAPS is located at $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}}) = (-5000, 100, 20000)$. The CS antenna gain and each user antenna gain are considered $G^{\text{CS}} = 43.2$ dB, $G_j = 0$ dB $\forall j$, $G_i = 0$ dB $\forall i$, respectively. The system operates over a total bandwidth of $BW = 100$ MHz, equally divided between a UAV-based network and a HAPS-RIS-assisted network. It uses a carrier frequency of $f_c = 2$ GHz and $L = 64$ subcarriers for communication. The reflection loss corresponding to each RIS element is considered $\mu_m = 1, \forall m$. The noise power spectral density is $N_0 = -174$ dBm/Hz, the path loss exponent is $\alpha = 2$, and the excessive path loss coefficients for LoS and NLoS are $\eta_1 = 1$ and $\eta_2 = 31$, respectively. The constant values which depend on the environment type are considered $\psi = 5$ and $\beta = 0.5$. The CS transmit power is 40 dBm except the results where its value is

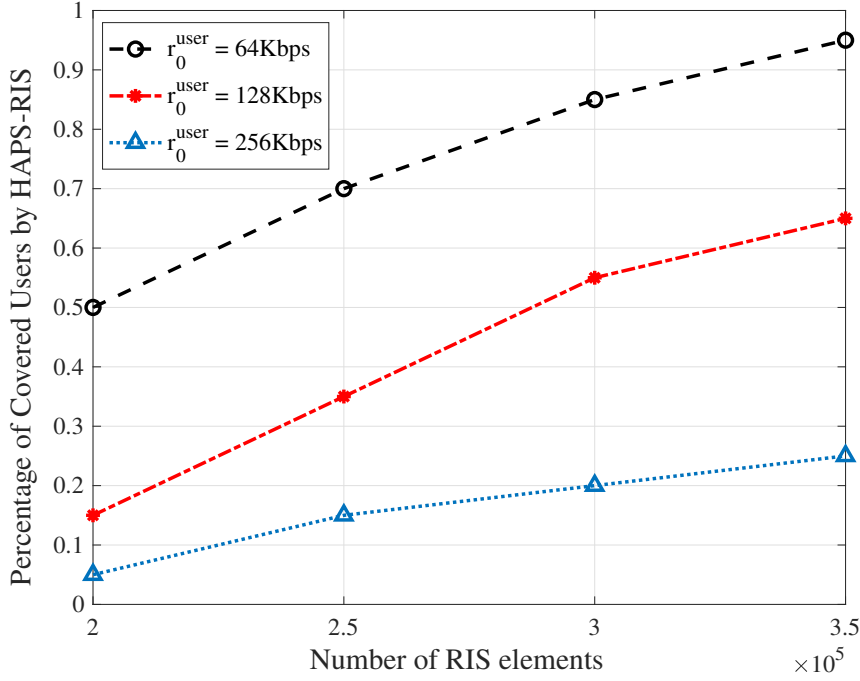


Fig. 4.3 Percentage of covered users by HAPS-RIS versus number of RIS element for the rate requirements 64, 128, and 256 kbps when the CS transmit power is 40 dBm and only HAPS-RIS setup is in use.

mentioned and the transmit power of each UAV is 20 dBm. The results are averaged over a large number of simulation runs.

Fig. 4.3, Fig. 4.4, and Fig. 5.10 are results obtained by solving the leader problem **OP 1** by exploiting the proposed DyRaZARC technique when there is only HAPS-RIS to support the users. Fig. 4.3 and Fig. 4.4 are the results where a portion of the coverage area is covered by HAPS-RIS and the rest of the users are in the outage. Fig. 5.10 demonstrates the result where full coverage is provided only by HAPS-RIS system. Fig. 4.6 is the result obtained by exploiting the proposed DyRaZARC and KADUS techniques to solve the leader and follower problems, i.e., **OP 1** and **OP 2**, respectively. In this case, full coverage is provided by integration of two types of infrastructures, i.e., UAVs and HAPS-RIS system. We take into account a wide range of rate requirements, spanning from kbps to Mbps.

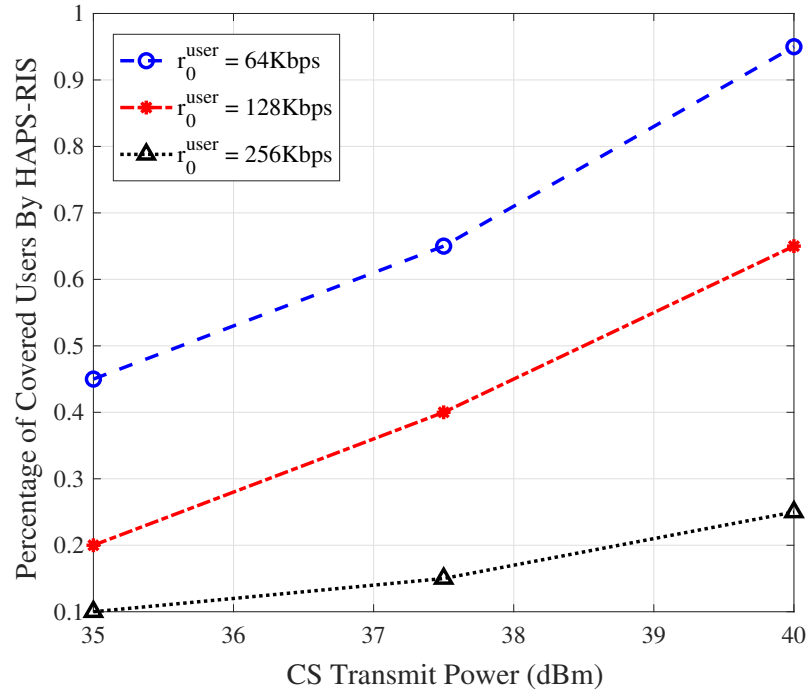


Fig. 4.4 Percentage of covered users by HAPS-RIS versus CS Transmit power for the rate requirements 64, 128, and 256 kbps when the number of RIS elements are 3.5×10^5 and only HAPS-RIS setup is in use.

4.4.1 Performance Evaluation of the Standalone HAPS-RIS Architecture

Fig. 4.3 demonstrates the percentage of users covered by HAPS-RIS versus the number of RIS elements for three different data rate thresholds of 64 kbps, 128 kbps, and 256 kbps. As the number of RIS elements increases, the percentage of covered users also rises across all data rate thresholds. For the lowest data rate of 64 kbps, user coverage begins at approximately 50% and approaches 90% as the number of RIS elements increases. For the 128 kbps threshold, coverage starts at around 20% and increases to about 60%. The highest data rate of 256 kbps shows the lowest coverage, beginning slightly above 10% and reaching around 30%. Fig. 4.4 demonstrate the percentage of users covered by HAPS-RIS versus the CS transmit power for various minimum data rate requirements, data rate thresholds of 64 kbps, 128 kbps, and 256 kbps, utilizing 3.5×10^5 RIS elements. The findings show that increasing CS transmit power leads to a higher percentage of covered users. These results underscore the pivotal role of both CS transmit power and the number of RIS elements in the coverage provided by HAPS-RIS. Fig. 5.10 shows that as the minimum rate requirement r_0^{user}

increases, the number of RIS elements M needed for full coverage also rises, both on a logarithmic scale. This indicates that higher rate demands require more RIS elements. The result highlights the potential of the HAPS-RIS system to provide full coverage while satisfying different rate requirements without relying on UAVs.

4.4.2 Performance Evaluation of the Integrated HAPS-RIS and UAV Architecture

Fig. 4.6 presents the minimum number of required UAVs N^* versus the total number of RIS elements M to achieve the full coverage at different minimum rate requirements r_0^{user} . The graph depicts three distinct scenarios: $r_0^{\text{user}} = 2$ Mbps, $r_0^{\text{user}} = 4$ Mbps, and $r_0^{\text{user}} = 8$ Mbps. The stepped nature of each line indicates that as the number of RIS elements increases, the number of UAVs needed decreases in discrete steps. For the highest rate requirement, 8 Mbps, the system requires up to 4 UAVs when the number of RIS elements is low; however, as M increases beyond approximately 5 million elements, no UAVs are needed. Conversely, for lower rate requirements, 2 Mbps and 4 Mbps, fewer UAVs are required overall, and the need for UAVs is eliminated at a lower threshold of RIS elements. This analysis illustrates the trade-off between the number of RIS elements and UAVs: as the number of RIS elements increases, the dependence on UAVs decreases, which is particularly beneficial for meeting higher rate requirements with fewer UAVs.

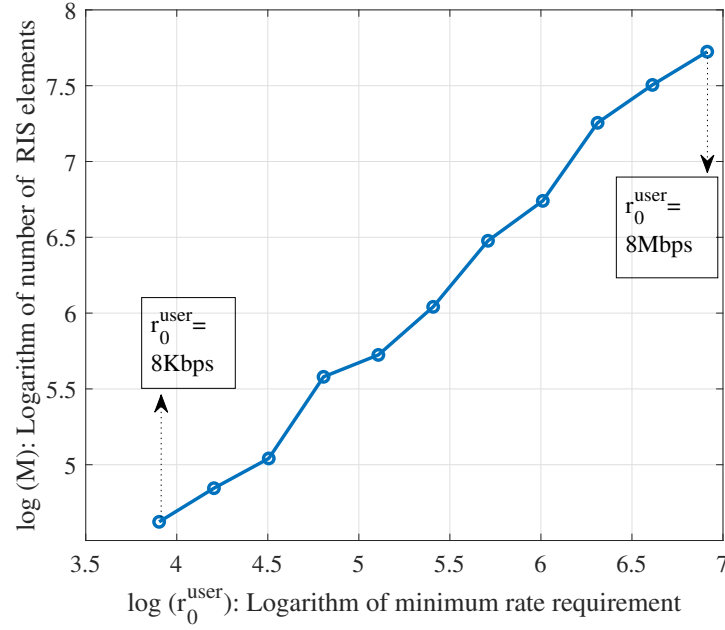


Fig. 4.5 Required number of total RIS elements in logarithmic scale versus logarithm of the minimum rate requirements to provide full coverage, where only HAPS-RIS setup is in use.

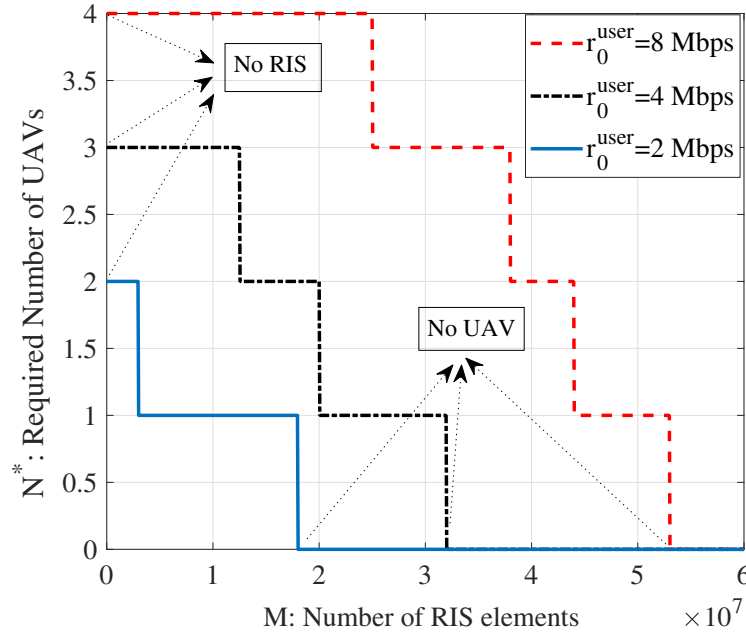


Fig. 4.6 Trade-off between the number of UAVs and RIS elements to provide the full coverage. This is achieved by exploiting the proposed DyRaZARC and KADUS techniques where both HAPS-RIS setup and UAVs are in use.

4.5 Lessons Learned and Conclusion

In this chapter, We addressed the second research question of this thesis where focus shifts from restoring connectivity to reshaping infrastructure. While previous chapter demonstrated that mobility can be analytically controlled at the link level, this chapter confronts a more structural question that what happens when the limitation is not the channel, but the infrastructure itself. In UAV-based networks, the scarcity of aerial nodes is often treated as an unavoidable constraint. By integrating aerostatic HAPS-RIS with UAV networks, a novel heterogeneous non-terrestrial architecture was introduced. Instead of increasing UAV density to meet user demand, the system strategically redistributes coverage responsibilities between tiers. A hierarchical bilevel optimization framework was formulated, where the leader problem determines the HAPS-RIS service region and configuration, and the follower problem minimizes the required number of UAVs through geometry-aware clustering. In this way, the rigid limitation on UAV availability was transformed into a controllable architectural trade-off.

The main lesson learned in this chapter is that infrastructure scarcity is not a fixed boundary, but a design variable when tiers cooperate. Instead of increasing network capacity by simply deploying more UAVs, the proposed hierarchical framework enables more efficient utilisation of aerial resources through coordination between the two tiers. Although the proposed architecture significantly improves resource allocation and network scalability, the interaction between the HAPS-RIS and UAV tiers remains hierarchical rather than fully integrated. In the next chapter, the focus shifts from hierarchical coordination between tiers to their full integration within a unified joint multi-objective optimization framework.

Chapter 5

HAPS-RIS and UAV Integrated Networks: A Unified Joint Multi-objective Framework

This chapter presents the third technical contribution of this PhD thesis and represents the architectural culmination of the ideas developed in the previous chapter. The integration of UAVs as active *network infrastructure* in aerostatic HAPS–RIS–assisted systems remains largely unexplored, as elaborated in Chapter 2 and Chapter 4. To the best of my knowledge, based on the literature surveyed in this thesis, the only existing study in this direction is the work presented in the previous chapter of this PhD thesis, published in [30], where a HAPS–RIS–assisted multi-UAV architecture is introduced and UAVs operate as aerial access nodes. While it establishes the feasibility of UAVs as infrastructure, it addresses only one challenge, namely the limitation on the number of UAVs. Other critical challenges such as UAV power-budget limitation and bandwidth limitation are left open and they are investigated in this chapter. Moreover, the previous chapter relies on a disjoint and hierarchical design, where the HAPS–RIS and UAV systems operate with dedicated bandwidth resources and are optimized sequentially, leaving joint bandwidth utilization and system-level coupling unaddressed. However, despite the effectiveness of hierarchical coordination, a structural separation between tiers still remained. This raises a deeper novel architectural research question which is “*How can aerostatic HAPS-RIS and UAV infrastructures be jointly designed within a unified system-level multiobjective framework?*”. To answer this question, this chapter proposes a novel joint multi-objective framework that removes the remaining boundaries between tiers and design variables. The aforementioned motivations,

challenges, and contributions of this chapter are summarized in Fig. 5.1. This technical contribution was recently submitted to the IEEE Transactions on Vehicular Technology (TVT).

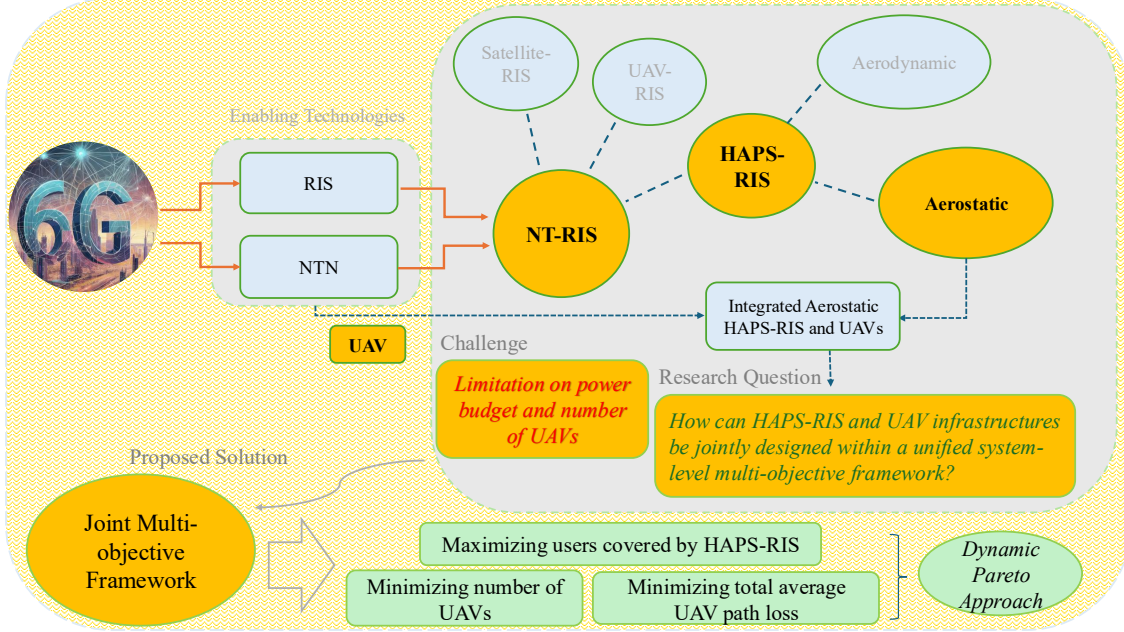


Fig. 5.1 Motivations and contributions of this chapter at a glance. The visual abstract depicts the conceptual flow of the chapter. Arrows indicate conceptual progression, not control-system signal flow.

5.1 The Main Contributions of this Chapter

The main contributions of this chapter are highlighted as follows:

5.1.1 A Comprehensive Unified System-level Framework

We introduce a novel unified system-level framework for integrating HAPS-RIS and UAV integrated network by designing a novel multi-objective joint optimization framework that tightly couples HAPS-RIS and UAV-based networks in non-terrestrial networks. To the best of my knowledge, based on the literature surveyed in this thesis, this architecture constitutes the most comprehensive system-level optimization framework for HAPS-RIS and UAV integrated networks, as benchmarked in Table 2.3.

5.1.2 A Low-Complexity Solution Strategy

We propose a novel solution strategy to reduce the original high-complexity optimization problem to a low-complexity framework through mathematical derivations provided in *Theorem 5.1*, *Lemma 5.1*, and *Proposition 5.1*. Then, We solve the relaxed optimization problem with the proposed dynamic Pareto optimization approach.

- We obtain a theoretical link between classical optimization and unsupervised learning, as proven in *Theorem 5.1*. We show that minimizing the upper bound of the total average UAV path loss is mathematically equivalent to performing k -means clustering as an unsupervised learning. This result allows the UAV deployment and user association problem to be solved through a clustering operation rather than optimization, effectively transforming the original three-objective formulation into a k -means-driven two-objective problem.
- We introduce a practical RIS phase-shift design, in *Lemma 5.1*, that leverages the geometric properties of the HAPS-RIS scenario to obtain a simple closed-form expression for the RIS phase shifts. This eliminates the need to optimize a massive number of RIS phase shifts and makes their design straightforwardly implementable.
- We propose a mapping technique, presented in *Proposition 5.1*, which transforms the high-dimensional combinatorial association problem into a low-dimensional formulation using zone-based association and bandwidth portioning variables.
- To solve the transformed optimization problem, We propose a network-aware dynamic Pareto optimization framework. The priority structure is not arbitrarily imposed but emerges naturally from the physical and operational characteristics of the network. In particular, prioritizing HAPS-RIS coverage is shown to be essential for fully exploiting its capability before relying on UAV deployment.
- We obtain the computational complexity and show that the proposed framework scales polynomially with the number of users, UAVs, subcarriers, and RIS elements, confirming its scalability for large-scale HAPS-RIS deployments.

5.1.3 System-Level Insights and Design Guidelines

Through extensive simulations, We provide rate regime design guidelines, benchmarking, and trade-offs for the proposed framework.

- We reveal a regime-dependent behavior in which HAPS-RIS suffices at low data rates, while higher rate regime necessitate UAV assistance.
- We show that all conventional baseline architectures emerge as special cases of the proposed framework through a novel design parameter termed the bandwidth portioning factor, which unifies HAPS-RIS and UAV-based deployments within a single formulation. We benchmark the proposed framework against baselines across a wide range of rate requirements, consistently demonstrating its superior performance.
- We reveal a quantifiable trade-off between UAV deployment and RIS size, where increasing RIS elements can effectively reduce the need for UAVs across different rate regimes.

5.2 The Proposed Network Architecture

We consider a downlink transmission scenario where heterogeneous non-terrestrial infrastructures, i.e., HAPS-RIS and UAVs, are exploited to bring connectivity to a remote area as shown in Fig. 5.2. It is assumed that the UAVs and the CS operate independently to provide connectivity and they are not connected to each other. Severe blockage eliminates the possibility of direct CS-user links, making the HAPS-RIS-assisted cascaded channel the only viable communication path. The set of stationary users $\mathcal{I}$ is defined as $\mathcal{I}=\{1, \dots, I\}$, where $i \in \mathcal{I}$ represents an individual user indexed by i . The users are uniformly distributed in a circular area, with a minimum separation distance of D_0 among them, where there is no nearby terrestrial infrastructure.

The set of UAVs $\mathcal{J}$ is defined as $\mathcal{J} = \{1, \dots, J\}$, where $j \in \mathcal{J}$ represents an individual UAV indexed by j . In this scenario, UAVs act as hovering aerial base stations. In HAPS-RIS scenarios, CS uses high gain directional antenna, creating a dominated LoS connection with HAPS [28, 29, 64–67]. The set of RIS elements $\mathcal{M}$ is defined as $\mathcal{M} = \{1, \dots, M\}$, where $m \in \mathcal{M}$ represents the RIS element indexed by m . Users can be connected to the network either through the UAV system or the HAPS-RIS setup, but not through both at the same time. The coverage area is a circle with the radius R_0 with the centre of (x_0, y_0, z_0) , the CS location is $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}})$, the location of the HAPS is $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}})$, and the location of the UAV j is $(x_j^{\text{UAV}}, y_j^{\text{UAV}}, z_j^{\text{UAV}})$ in the Cartesian coordinate system. The set of equally spaced orthogonal subcarriers L is defined as $L=\{1, \dots, L^{\text{tot}}\}$, where $l \in L$ represents the

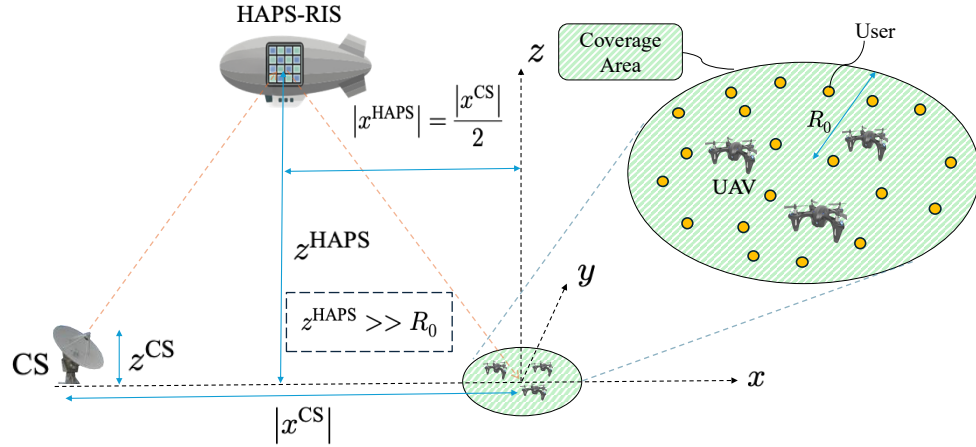


Fig. 5.2 The Proposed System Model

subcarrier indexed by l . The system bandwidth BW is divided into L^{tot} equally spaced and orthogonal subcarriers to be shared between the CS and the UAVs for serving the users. Therefore, the bandwidth allocated to each orthogonal subcarrier is $B_l = \frac{BW}{L^{\text{tot}}}$.

5.2.1 UAV-based Network Architecture

We consider a cellular scenario where the users covered by multiple UAVs are using orthogonal frequency division multiple access (OFDMA), and hence, there are multi-cells where there is inter-cell interference but no intra-cell interference. The signal to interference plus noise ratio (SINR) of the user i served by UAV j over subcarrier l' can be obtained as

$$\gamma_{ij}^{l', \text{UAV}} = \frac{P_{ij}^{l', \text{UAV}} \tilde{\rho}_{ij}^{l', \text{UAV}} |h_{ij}^{\text{UAV}}|^2}{N_0 B_{l'} + \sum_{j' \neq j}^J P_{ij'}^{l', \text{UAV}} \tilde{\rho}_{ij'}^{l', \text{UAV}} |h_{ij'}^{\text{UAV}}|^2}, \forall i, \forall j, l' \quad (5.1)$$

where N_0 is the noise power spectral density and $P_{ij}^{l', \text{UAV}}$ is the transmit power of the UAV j allocated to the subcarrier l' and the user i . $\tilde{\rho}_{ij}^{l', \text{UAV}}$ is a binary variable where $\tilde{\rho}_{ij}^{l', \text{UAV}} = 1$ indicates that subcarrier l' of UAV j is assigned to user i , while $\tilde{\rho}_{ij}^{l', \text{UAV}} = 0$ otherwise. h_{ij}^{UAV} is the channel gain between user i and UAV j , which can be formulated as $h_{ij}^{\text{UAV}} = \sqrt{G_j^{\text{UAV}} G_i \bar{\mathcal{L}}_{ij}^{-1}}, \forall i, j$. G_j^{UAV} is the antenna gain of the UAV j , G_i is the antenna gain of the user i , and $\bar{\mathcal{L}}_{ij}$ is the average path loss between user i

and UAV j which can be obtained as [84]

$$\bar{\mathcal{L}}_{ij} = P_{ij,\text{LoS}}^{\text{UAV}} \eta_1 \left(\frac{4\pi f_c}{c} d_{ij} \right)^\alpha + P_{ij,\text{NLoS}}^{\text{UAV}} \eta_2 \left(\frac{4\pi f_c}{c} d_{ij} \right)^\alpha, \forall i, j, \quad (5.2)$$

where f_c is the carrier frequency and c is the speed of wave propagation which is considered to be equal to the speed of light. α is the path loss exponent, and η_1 and η_2 are the excessive path loss coefficients for LoS and non-LoS (NLoS) connections, respectively. The distance between user i and UAV j can be formulated as

$$d_{ij} = \sqrt{(x_i - x_j^{\text{UAV}})^2 + (y_i - y_j^{\text{UAV}})^2 + (z_i - z_j^{\text{UAV}})^2}, \forall i, j. \quad (5.3)$$

$P_{ij,\text{LoS}}^{\text{UAV}}$ is the LoS probability between the user i and the UAV j as $P_{ij,\text{LoS}}^{\text{UAV}} = \frac{1}{1 + \psi e^{-\beta(\tilde{\theta}_{ij} - \psi)}}$, $\forall i, j$, where β and ψ are the constant values that depend on the environment type, $P_{ij,\text{LoS}}^{\text{UAV}} + P_{ij,\text{NLoS}}^{\text{UAV}} = 1, \forall i, \forall j$, and $\tilde{\theta}_{ij} = \frac{180}{\pi} \arcsin\left(\frac{z_j^{\text{UAV}}}{d_{ij}}\right), \forall i, \forall j$.

5.2.2 HAPS-RIS assisted Network Architecture

In the HAPS-RIS assisted network, CS communicates with the users through HAPS-RIS. The coordinates of the CS, user i , HAPS, and RIS element m , are $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}})$, (x_i, y_i, z_i) , $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}})$, $(x_m^{\text{RIS}}, y_m^{\text{RIS}}, z_m^{\text{RIS}})$, respectively. To define the channel, We consider h_{im}^{CS} as the cascade channel gain between user i -RIS and RIS-CS through RIS element m .

$$h_{im}^{\text{CS}} = \sqrt{G^{\text{CS}} G_i (\mathcal{L}_m^{\text{CS-RIS}})^{-1} (\mathcal{L}_{im}^{\text{RIS-user}})^{-1}}, \forall m, i, \quad (5.4)$$

where G^{CS} is the antenna gain of the CS and G_i is the antenna gain of the user i . Using the Friis model, [41], the path loss between CS and RIS element m can be formulated as

$$\mathcal{L}_m^{\text{CS-RIS}} = \left(\frac{4\pi f_c}{c} \right)^2 \times \left((x_m^{\text{RIS}} - x^{\text{CS}})^2 + (y_m^{\text{RIS}} - y^{\text{CS}})^2 + (z_m^{\text{RIS}} - z^{\text{CS}})^2 \right), \forall m, \quad (5.5)$$

and the path loss between RIS element m and the user i can be formulated as

$$\mathcal{L}_{im}^{\text{RIS,user}} = \left(\frac{4\pi f_c}{c} \right)^2 \times \left((x_m^{\text{RIS}} - x_i)^2 + (y_m^{\text{RIS}} - y_i)^2 + (z_m^{\text{RIS}} - z_i)^2 \right), \forall m, i, \quad (5.6)$$

The beyond cell users, which are covered by HAPS-RIS, are orthogonal to each other and to the cellular users served by the UAVs. Hence, there is no inter-user interference. The signal to noise ratio (SNR) of the received signal at user i and subcarrier l , can be obtained as

$$\gamma_i^{l,\text{CS}} = \frac{P_i^{l,\text{CS}} \left| \sum_{m=1}^M \rho_{im}^{l,\text{CS}} h_{im}^{\text{CS}} \vartheta_{im} \right|^2}{N_0 B_l}, \forall i, l, \quad (5.7)$$

where M is the total number of RIS elements and $P_i^{l,\text{CS}}$ denotes the transmit power allocated by the CS to the user i over the subcarrier l . $\rho_{im}^{l,\text{CS}}$ is the binary variable which demonstrates the RIS element m is assigned to the user i over subcarrier l . Considering ϑ_{im} as the reflection coefficient of the RIS element m corresponding to the user i as

$$\vartheta_{im} = \mu_m e^{-j(\phi_m - \xi_m^{\text{CS}} - \omega_{im})}, \forall i, m, \quad (5.8)$$

where $\phi_m \in [0, 2\pi]$ is the RIS phase shift for the element m . ξ_m^{CS} is the corresponding phase between the RIS element m and the CS. ω_{im} is the corresponding phase between RIS element m and the user i . $0 \leq \mu_m \leq 1$ is the reflection loss corresponding to the RIS element m .

5.3 The Proposed Multi-objective Joint Optimization Problem

To fully integrate the HAPS-RIS and UAV-based network architectures, We propose a multi-objective joint optimization problem that simultaneously considers the key parameters of both infrastructures. The objective functions include: (i) the number of users covered by the HAPS-RIS system, (ii) the required number of UAVs and (iii) the total average air-to-ground path loss experienced by users served by UAVs. These objectives reflect the dual nature of the integrated system, where the first objective corresponds to the HAPS-RIS setup and the latter two are associated with the UAV network.

Definition 5.1: The total number of users covered by the HAPS-RIS is obtained by counting the number of users that are assigned to at least one RIS element on at least one subcarrier. User i is considered covered by the HAPS-RIS if there exists *any* RIS element m and *any* subcarrier l such that $\rho_{im}^{l,\text{CS}} = 1$. While $\rho_{im}^{l,\text{CS}} = 0$ means that no transmission is scheduled for this user-RIS-subcarrier combination. Based on

this rule, the total number of HAPS-RIS-served users can be obtained as

$$U^{\text{HAPS}} = \sum_{i \in \mathcal{I}} \max_{\forall m, l} \rho_{im}^{l, \text{CS}}, \quad (5.9)$$

where the inner maximization checks whether user i is assigned to at least one RIS element and one subcarrier.

Definition 5.2: The total average path loss between UAVs and ground users is obtained by aggregating the path loss values over all UAV-user pairs that are actually assigned to at least one subcarrier. The total average UAV path loss over all associated UAV-user pairs is obtained as

$$\Lambda^{\text{UAV}} = \sum_{i \in \mathcal{I}} \sum_{j \in \mathcal{J}} (\max_{\forall l'} \tilde{\rho}_{ij}^{l', \text{UAV}}) \bar{\mathcal{L}}_{ij}, \quad (5.10)$$

where the inner maximization term acts as an association indicator; it is equal to one if user i is served by UAV j on at least one subcarrier, and zero if no subcarrier of UAV j is allocated to user i . $\bar{\mathcal{L}}_{ij}$ denotes the average path loss between UAV j and user i , obtained in (5.2).

In the proposed multi-objective joint optimization framework, We aim to maximize the number of covered users by the HAPS-RIS, minimize the number of required UAVs, and minimize the overall average UAV path loss. The optimization variables associated with the UAV setup include the two-dimensional placement of the UAVs, i.e., their latitude and longitude, the binary association indicators for the UAV-user-subcarrier assignments, and the number of UAVs required to serve the users. The optimization variables associated with the HAPS-RIS setup include the binary association indicators for the HAPS-RIS subcarrier-user-RIS element assignments and the RIS phase-shifts. The constraints ensure that all users satisfy their quality-of-service (QoS) requirements, that the power budget limitations at both the CS and the UAVs are met, and that the OFDMA-based orthogonality and user-association rules are guaranteed. The main optimization problem can be designed as

$$\text{OP 1: } \max_{\mathbf{X}^{\text{UAV}}, \mathbf{Y}^{\text{UAV}}, \boldsymbol{\rho}^{\text{CS}}, \tilde{\boldsymbol{\rho}}^{\text{UAV}}, N^{\text{UAV}}, \phi} [U^{\text{HAPS}}, -N^{\text{UAV}}, -\Lambda^{\text{UAV}}] \quad (5.11a)$$

$$\text{s.t. } \tilde{\rho}_{ij}^{l', \text{UAV}}, \rho_{im}^{l, \text{CS}} \in \{0, 1\} \quad \forall i, j, m, l, l', \quad (5.11b)$$

$$\sum_{j=1}^{N^{\text{UAV}}} \sum_{l'=1}^{L^{\text{tot}}} \log_2 \left(1 + \gamma_{ij}^{l', \text{UAV}} \right) + \sum_{l=1}^{L^{\text{tot}}} \log_2 \left(1 + \gamma_i^{l, \text{CS}} \right) \geq r_0^{\text{user}} \quad \forall i \in \mathcal{I}, \quad (5.11c)$$

$$\rho_{im}^{l, \text{CS}} + \sum_{j=1}^J \tilde{\rho}_{ij}^{l', \text{UAV}} \leq 1 \quad \forall i, l, l', m, \quad (5.11d)$$

$$\sum_{i=1}^I \sum_{m=1}^M \sum_{l=1}^{L^{\text{tot}}} P_i^{l, \text{CS}} \rho_{im}^{l, \text{CS}} \leq P_{\max}^{\text{CS}}, \quad (5.11e)$$

$$\sum_{i=1}^I \sum_{l'=1}^{L^{\text{tot}}} P_{ij}^{l', \text{UAV}} \tilde{\rho}_{ij}^{l', \text{UAV}} \leq P_{\max}^j \quad \forall j, \quad (5.11f)$$

$$\rho_{im}^{l, \text{CS}} + \rho_{i'm}^{\tilde{l}, \text{CS}} \leq 1 \quad \forall i \neq i', l, \tilde{l}, m, \quad (5.11g)$$

$$\sum_{i=1}^I (\rho_{im}^{l, \text{CS}} + \tilde{\rho}_{ij}^{l', \text{UAV}}) \leq 1 \quad \forall l, l', j, m, \quad (5.11h)$$

where $\mathbf{X}^{\text{UAV}} = [x_1^{\text{UAV}}, \dots, x_{N^{\text{UAV}}}^{\text{UAV}}]_{1 \times N^{\text{UAV}}}$ and $\mathbf{Y}^{\text{UAV}} = [y_1^{\text{UAV}}, \dots, y_{N^{\text{UAV}}}^{\text{UAV}}]_{1 \times N^{\text{UAV}}}$ are the vectors representing the latitudes and longitudes of the UAVs, respectively. Constraint (5.11b) demonstrates the binary variables. Constraint (5.11c) ensures that the data rate received by each user meets the minimum data rate requirement where the minimum threshold is r_0^{user} for all the users. Although (5.11c) includes both the HAPS-RIS and UAV rate terms, a user cannot be served by both simultaneously. The inequality (5.11d) guarantees that each user can be connected to either HAPS-RIS setup or a UAV, but not both of them. Thus, each user is linked either to the HAPS-RIS or to a single UAV, and the other rate term in (5.11c) becomes zero accordingly. Furthermore, (5.11d) ensures that each user can not be connected to more than one UAV. In (5.11e), We ensure that the total transmission power allocated to users covered by the HAPS-RIS setup does not exceed $P_{\max}^{\text{CS}}$ which is the maximum power limit of the CS. In (5.11f), We ensure that the total transmission power allocated to the users supported by the UAV j does not exceed $P_{\max}^j$ which is the maximum power limit of the UAV j . Constraint (5.11g) guarantees that each RIS element can not be assigned to more than one user. Given with the assumption that the single CS uses OFDMA, all the users covered by HAPS-RIS setup are considered as a single cell, so that there is no inter-user interference. Hence, a dedicated set of RIS units is allocated

to each user on its assigned subcarriers. This is because RIS elements can operate differently across frequencies [60]. Constraint (5.11h) guarantees that the subcarriers allocated to each of the users supported by HAPS-RIS are orthogonal to the subcarriers associated to other users. In addition, this constraint ensures that the subcarriers allocated to the users supported by HAPS-RIS are orthogonal to the subcarriers allocated to the UAVs. This assumption is in line with the assumptions in HAPS-RIS scenarios, [30, 65], where the CS is considered as the auxiliary infrastructure providing a beyond cell over the existing network. Furthermore, this constraint guarantees that the allocated subcarriers to each UAV are orthogonal to other UAVs' assigned subcarrier. This is because We consider UAVs use OFDMA so that there is no intra-cell interference but there is inter-cell interference.

The proposed optimisation framework focuses on the access network which is the scope of this chapter, and hence, the backhaul connectivity is not considered. The availability and capacity of the backhaul links may influence the overall network performance in practical deployments. The proposed framework assumes fixed homogeneous users, homogeneous UAVs, homogeneous rate requirements, and sufficient backhaul connectivity. These assumptions are adopted to obtain a tractable optimisation framework while capturing the main design variables of the proposed architecture. Practical aspects such as backhaul-included and fully heterogeneous scenarios are left open for future work.

5.4 The Proposed Solution Method

The proposed optimization problem **OP 1** is a large-scale mixed-integer nonlinear program (MINLP) formulated as a multi-objective joint design over tightly coupled variables. These variables include the two-dimensional placement of UAVs, the required number of UAVs, the RIS phase shifts, and the user association indicators across UAVs, RIS elements, and subcarriers. The heterogeneous nature of the integrated HAPS-RIS and UAV architecture, combined with the massive number of RIS elements, users, and subcarriers, renders **OP 1** a high-dimensional and highly non-convex MINLP. Such formulations are well known to be NP-hard, making the computation of an exact optimal solution intractable. The intrinsic complexity of **OP 1** stems from three tightly coupled components. The UAV placement problem introduces a non-convex continuous optimization challenge, as the UAV channel gains are functions of the UAV locations and are jointly coupled with communication performance. The RIS phase-shift design further increases the dimensionality of the problem due to the

need to jointly optimize a massive number of reflecting elements. In addition, the user association decisions give rise to three-dimensional binary assignment structures, namely user–subcarrier–RIS element and user–subcarrier–UAV associations, resulting in a high dimensional combinatorial optimization. To overcome this intractability, my goal in this section is to provide a sequence of transformations included in *Theorem 5.1*, *Lemma 5.1*, and *Proposition 5.1*, which relax and map **OP 1** into a tractable optimization problem. This principled sequence of analytical transformations provides a clear pathway from the original NP-hard formulation to a low-complexity solution framework.

5.4.1 Proposed Upper Bound and k -Means Equivalence

Theorem 5.1: **OP 1** can be relaxed into **OP 2** with two objective functions as

$$\mathbf{OP\ 2} : \max_{\rho^{\text{CS}}, \tilde{\rho}^{\text{UAV}}, N^{\text{UAV}}, \phi} [U^{\text{HAPS}}, -N^{\text{UAV}}] \quad (5.12a)$$

$$\text{s.t. : (5.11b) – (5.11h)} \quad (5.12b)$$

where X^{UAV} , Y^{UAV} and $\zeta_{ij} = \max_{\forall l'} \tilde{\rho}_{ij}^{l', \text{UAV}}$ can be obtained based on k -means clustering operator, with the k factor equal to N^{UAV} . Since the upper bound of (5.10) is minimized through the k -means clustering operator, the third objective function of **OP 1** no longer needs to be included. This Theorem is valid for $\alpha = 2$ and the fixed UAV altitudes.

Proof In order to relax the third objective function, the aim is to obtain an upper bound for Λ^{UAV} . By substituting (5.2) into (5.10), We have

$$\Lambda^{\text{UAV}} = \sum_i \sum_j \zeta_{ij} (P_{ij, \text{LoS}}^{\text{UAV}} \eta_1 + P_{ij, \text{NLoS}}^{\text{UAV}} \eta_2) \left(\frac{4\pi f_c}{c} d_{ij} \right)^\alpha. \quad (5.13)$$

Due to the fact that $1 \geq P_{ij, \text{LoS}}^{\text{UAV}}, P_{ij, \text{NLoS}}^{\text{UAV}} \geq 0$, $\forall i, j$, and $\eta_2 > \eta_1$ We have

$$P_{ij, \text{LoS}}^{\text{UAV}} \eta_1 + P_{ij, \text{NLoS}}^{\text{UAV}} \eta_2 = P_{ij, \text{LoS}}^{\text{UAV}} \eta_1 + (1 - P_{ij, \text{LoS}}^{\text{UAV}}) \eta_2 = P_{ij, \text{LoS}}^{\text{UAV}} (\eta_1 - \eta_2) + \eta_2 \leq \eta_2, \quad (5.14)$$

By substituting (5.14) into (5.13), it can be observed that for $\alpha = 2$, the fixed UAV altitudes $z_j = z_{0, \text{UAV}}, \forall j$, without loss of generality by considering $z_i = 0, \forall i$, and given the fact that $0 \leq \zeta_{ij} \leq 1, \forall i, j$, and $N^{\text{UAV}} \leq N^{\text{UAV}, (0)}$, the upper bound of (5.13) can

be obtained as

$$\Lambda^{\text{UAV,upp}} = \eta_2 \left(\frac{4\pi f_c}{c} \right)^2 \left(z_{0,\text{UAV}}^2 I N^{\text{UAV},(0)} + \sum_i \sum_j^{N^{\text{UAV}}} \zeta_{ij} ((x_i - x_j)^2 + (y_i - y_j)^2) \right), \quad (5.15)$$

Interestingly, it can be observed that minimizing (5.15) is equivalent to run the k -means clustering as

$$\min \Lambda^{\text{UAV,upp}} \triangleq \eta_2 \left(\frac{4\pi f_c}{c} \right)^2 \times \underbrace{\left(\min_{\forall x_j \in X, \forall y_j \in Y, \zeta_{ij}} \sum_i \sum_j^{N^{\text{UAV}}} \zeta_{ij} ((x_i - x_j)^2 + (y_i - y_j)^2) \right)}_{k\text{-means clustering}}, \quad (5.16)$$

where the k factor is equal to N^{UAV} and cluster centers are UAV locations. Each user i is assigned to its nearest cluster center, which determines its serving UAV. Hence, the cluster membership indicator plays the role of the UAV–user association variable, i.e., $\zeta_{ij} = 1$ if user i belongs to the cluster associated with UAV j , and $\zeta_{ij} = 0$ otherwise. This mapping reveals that minimizing the sum of squared distances in k -means is equivalent to minimizing the upper bound of the total average UAV path loss in (5.10). Therefore, once k -means is applied for a given N_{UAV} , the UAV latitude and longitudes and UAV–user associations become deterministic outputs rather than optimization variables. As the upper bound of the (5.10) is minimized via k -means clustering, **OP 1** can be relaxed into **OP 2**.

5.4.2 Proposed Practical RIS Phase Shift Design

Although **OP 2** already reduces the complexity of the main optimization problem, it remains a large-scale non-convex MINLP, and hence, NP-hard. Owing to the fact that there are massive number of RIS elements in the HAPS-RIS scenarios, obtaining the optimal RIS phase shifts in this high complexity problem leads to huge computational overhead which is intractable. Hence, the target in this step is to define a practical RIS phase shift design to relax **OP 2** into a problem with a lower computational complexity.

Lemma 5.1: **OP 2** can be relaxed into

$$\textbf{OP 3 : } \max_{\boldsymbol{\rho}^{\text{CS}}, \tilde{\boldsymbol{\rho}}^{\text{UAV}}, N^{\text{UAV}}} [U^{\text{HAPS}}, -N^{\text{UAV}}] \quad (5.17a)$$

$$\text{s.t. : (5.11b) – (5.11h)} \quad (5.17b)$$

with the proposed practical RIS phase shift design $\phi_m^* = \xi_0 + \omega_0 + 2\tilde{k}\pi$, $\forall m$ where $\tilde{k}$ is an integer value.

Proof In the proposed geometrical case, the dimensions of RIS can be negligible compared to the altitude of HAPS, as it does not have much effect on the performance. Hence, without loss of generality, We relax the location of the RIS elements as $(x_m^{\text{RIS}}, y_m^{\text{RIS}}, z_m^{\text{RIS}}) \approx (x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}})$, $\forall m$.¹ The dimensions of the RIS and the coverage area is much less than the range of the distance between HAPS-RIS and the terrestrial components. Accordingly, without loss of generality, We can relax the corresponding phases to fixed values as $\xi_m^{\text{CS}} \approx \xi_0, \forall m$ and $\omega_{im} \approx \omega_0, \forall i \in \mathcal{C}, \forall m$, so the reflection gain of RIS element m can be relaxed as $\vartheta_{im} \approx \tilde{\vartheta}_m, \forall i \in \mathcal{C}, \forall m$ where

$$\tilde{\vartheta}_m = \mu_m e^{-j(\phi_m - \xi_0 - \omega_0)} \quad \forall m. \quad (5.18)$$

As (5.18) is independent from user index, $r_i^{\text{CS}}(R, \tilde{\vartheta}_m)$ can be relaxed into its upper bound by considering $\phi_m^* = \arg \max \tilde{\vartheta}_m = \xi_0 + \omega_0 + 2\tilde{k}\pi, \forall m$. Accordingly, (5.12b) is relaxed into (5.17b) and hence **OP 2** is relaxed into **OP 3**. This provides a practical implementation approach, given the massive number of RIS elements in HAPS-RIS scenario.

5.4.3 Proposed Mapping Technique

Although **OP 3** significantly reduces the dimensionality of the original formulation, it remains a large-scale non-convex MINLP and is therefore still NP-hard. The remaining complexity arises from the combinatorial user-UAV-subcarrier and user-subcarrier-RIS-element association variables. Jointly optimizing these discrete assignments is computationally prohibitive. To obtain a tractable problem while preserving the essential coupling between the HAPS-RIS and UAV infrastructures, We introduce a new set of geometric and bandwidth-related optimization variables and map the combinatorial associations in **OP 3** into these lower-dimensional variables. This leads to the proposed optimization problem **OP 4**, stated below.

¹The dimensions of the RIS are in the range of 100 meters while the HAPS-to-CS and HAPS-to-users distances are in the range of more than 20 kilometers.

Proposition 5.1: **OP 3** can be relaxed and mapped into **OP 4** as

$$\mathbf{OP\ 4} : \max_{R, N^{\text{UAV}}, \kappa} [\tilde{U}^{\text{HAPS}}, -N^{\text{UAV}}] \quad (5.19a)$$

$$\text{s.t. } \tilde{\rho}_{ij}^{l^u, \text{UAV}} \in \{0, 1\}, \forall i \in \mathcal{B}, j, l^u, \quad (5.19b)$$

$$\tilde{\rho}_{im}^{l^c, \text{CS}} \in \{0, 1\}, \forall i \in \mathcal{C}, m, l^c, \quad (5.19c)$$

$$\sum_{j=1}^{N^{\text{UAV}}} \sum_{l^u=1}^{L^{\text{UAV}}} \log_2 \left(1 + \tilde{\gamma}_{ij}^{l^u, \text{UAV}} \left(R, N^{\text{UAV}}, \kappa \right) \right) \geq r_0^{\text{user}}, \forall i \in \mathcal{B}, \quad (5.19d)$$

$$\sum_{l^c=1}^{L^{\text{CS}}} \log_2 \left(1 + \tilde{\gamma}_i^{l^c, \text{CS}}(R, \kappa) \right) \geq r_0^{\text{user}} \forall i \in \mathcal{C}, \quad (5.19e)$$

$$\sum_{j=1}^{N^{\text{UAV}}} \tilde{\rho}_{ij}^{\text{UAV}, l^u} \left(R, N^{\text{UAV}}, \kappa \right) \leq 1 \quad \forall i \in \mathcal{B}, l^u, l^{u'}, \quad (5.19f)$$

$$\sum_{\forall i \in \mathcal{C}} \sum_{m=1}^M \sum_{l^c=1}^{L^{\text{CS}}} P_i^{l^c, \text{CS}} \tilde{\rho}_{im}^{l^c, \text{CS}}(R, \kappa) \leq P_{\max}^{\text{CS}}, \quad (5.19g)$$

$$\sum_{\forall i \in \mathcal{B}} \sum_{l^u=1}^{L^{\text{UAV}}} P_{ij}^{l^u, \text{UAV}} \tilde{\rho}_{ij}^{l^u, \text{UAV}}(R, N^{\text{UAV}}, \kappa) \leq P_{\max}^j \forall j, \quad (5.19h)$$

$$\tilde{\rho}_{im}^{l^c, \text{CS}}(R, \kappa) + \tilde{\rho}_{i'm}^{l^{c'}, \text{CS}}(R, \kappa) \leq 1 \quad \forall (i \neq i') \in \mathcal{C}, l^c, l^{c'}, m, \quad (5.19i)$$

$$\sum_{\forall i \in \mathcal{C}} \tilde{\rho}_{im}^{l^c, \text{CS}}(R, \kappa) \leq 1 \quad \forall l^c, m, \quad (5.19j)$$

$$\sum_{\forall i \in \mathcal{B}} \tilde{\rho}_{ij}^{l^u, \text{UAV}}(R, N^{\text{UAV}}, \kappa) \leq 1 \quad \forall l^u, j, \quad (5.19k)$$

where R is the radius of the UAV zone, which is illustrated in the proposed geometric model in Fig. 5.3. $\kappa = \frac{L^{\text{CS}}}{L^{\text{UAV}}}$ is the BW portioning factor where $L^{\text{CS}} = \frac{\kappa}{\kappa+1} L^{\text{tot}}$ and $L^{\text{UAV}} = \frac{1}{\kappa+1} L^{\text{tot}}$ are the number of orthogonal subcarriers allocated to CS and UAVs, respectively, while $L^{\text{tot}} = L^{\text{CS}} + L^{\text{UAV}}$. The combinatorial optimization variables of **OP 3** are relaxed and mapped into new optimization variables R and κ and the constraints of **OP 3** in (5.11b)-(5.11h) are mapped as follows: (5.11b) $\rightarrow$ (5.19b)-(5.19c); (5.11c) $\rightarrow$ (5.19d)-(5.19e); (5.11d) $\rightarrow$ (5.19f); (5.11e) $\rightarrow$ (5.19g); (5.11f) $\rightarrow$ (5.19h); (5.11g) $\rightarrow$ (5.19i); (5.11h) $\rightarrow$ (5.19j)-(5.19k), and the objective function (5.9) is transformed into $\tilde{U}^{\text{HAPS}}(R, \kappa)$.

Proof The key difficulty in **OP 3** lies in the three-dimensional binary association variables $\rho_{im}^{l,CS}$ and $\tilde{\rho}_{ij}^{l,UAV}$, which jointly determine the user–RIS–subcarrier and user–UAV–subcarrier assignments, respectively. Since these variables scale with the number of users, UAVs, RIS elements, and subcarriers, their joint optimization results in an exponentially large combinatorial search space. To construct a tractable reformulation, We exploit the geometric structure of the integrated HAPS–RIS and UAV system and map these high-dimensional variables into scalar variables.

1) *Zone-based mapping of user associations:* As illustrated in Fig. 5.3, the coverage region is partitioned into two zones: an inner circular region of radius R , called *UAV zone*, which is presented by the set $\mathcal{B} \subseteq \mathcal{I}$, and an outer ring between the main coverage and the UAV zone, called *HAPS–RIS zone*, which is presented by the set $\mathcal{C} = \mathcal{I} \setminus \mathcal{B}$. All users in $\mathcal{C}$ are served by the HAPS–RIS and all users in $\mathcal{B}$ are served by the UAVs. Due to the very large HAPS altitude relative to the ground coverage radius, the channel gain between the HAPS–RIS and any ground user depends almost entirely on the HAPS altitude and is only marginally affected by the exact choice of user. Hence, the precise user association has negligible impact on performance. This allows us to replace the user-level association variables with the zone-level indicator.

2) *Bandwidth portioning-based mapping of subcarrier allocations:* All UAVs are assumed to be homogeneous, operating at the same altitude with identical transmit powers, and all users have the same minimum rate requirement. The HAPS–RIS operates at a much higher altitude, and the CS has a different transmit-power budget than the UAVs. Moreover, users in the HAPS–RIS zone experience nearly symmetric channel conditions because the HAPS altitude is far greater than the coverage radius, making the impact of their exact locations negligible. Therefore, the detailed subcarrier assignment can be relaxed, and only the main heterogeneous factor distinguishing the two infrastructures, i.e., the bandwidth portioning ratio $\varkappa$ between the HAPS–RIS and UAVs, is retained. The total bandwidth is partitioned into two orthogonal sub-bands corresponding to the UAV-served users and the HAPS–RIS-served users. This partitioning follows from the fact that the users of two zones are orthogonal to each other. Hence, the users do not interfere with one another. On this basis, We define two disjoint subcarrier sets $L^{UAV} = \{1, \dots, L^{UAV}\}$, $L^{CS} = \{1, \dots, L^{CS}\}$, where $\varkappa = \frac{L^{CS}}{L^{UAV}}$, $L^{tot} = L^{CS} + L^{UAV}$, $L^{UAV} = \frac{1}{\varkappa+1} L^{tot}$ is the number of orthogonal subcarriers allocated to the UAV zone, and $L^{CS} = \frac{\varkappa}{\varkappa+1} L^{tot}$ is the number of subcarriers allocated to the HAPS–RIS zone. The two sets are mutually exclusive, i.e., $L^{UAV} \cap L^{CS} = \emptyset$ and $L^{UAV} \cup L^{CS} = L^{tot}$. This ensures that users in the HAPS–RIS zone and those in the UAV zone are served over orthogonal sub-bands without mutual interference. The

bandwidth portioning variable $\varkappa$ thus encapsulates the resource coupling between the two infrastructures, while eliminating the need for combinatorial subcarrier allocations.

3) *RIS clustering and association*: Following the RIS-clustering strategy adopted in [66], each user in the HAPS–RIS zone is assigned a dedicated cluster of RIS elements. Given that the HAPS altitude is vastly larger than the maximum distance between RIS clusters, the choice of a specific RIS cluster has a negligible impact on the resulting channel gain. Consequently, the users in the HAPS–RIS zone are assigned to RIS clusters through a random injective mapping without loss of generality.

Combining the above, the only remaining optimization variables are the scalar-valued decision variables R , N^{UAV} , and $\varkappa$, while all associations are deterministic functions of these variables. Hence, **OP 3** can be mapped into **OP 4**, completing the proof.

5.4.4 Proposed Dynamic Pareto Optimization Framework

The proposed geometric model of **OP 4** is illustrated in Fig. 5.3, while the building blocks and the interfaces of the proposed dynamic Pareto optimization framework are shown in Fig. 5.4. **OP 4** is a joint multi-objective optimization problem in which the HAPS–RIS and UAV systems are coupled through the bandwidth portioning factor. This coupling variable determines the bandwidth portions which are allocated to the HAPS–RIS setup and UAV-based networks. Therefore, the solution of **OP 4** is structured around $\varkappa$ as the *upper-layer* decision variable. For a given value of $\varkappa$, the objectives of **OP 4** are handled in the lower layer through a Pareto-based lexicographic optimizer [78]. At each iteration, a candidate bandwidth portioning factor is selected and passed to the Pareto optimization block in Fig. 5.4. For this fixed $\varkappa$, the lexicographic Pareto process evaluates the three objectives. We exploit pareto optimization, a hierarchical lexicographic approach. The highest priority is given to maximizing the number of users served by the HAPS–RIS setup. This is due to the fact that the HAPS–RIS is introduced as an assisting non-terrestrial component whose primary purpose is to enhance the existing UAV-based network. Giving the first priority to $\tilde{U}^{\text{HAPS}}$ ensures that the optimization fully exploits the HAPS–RIS capability before relying on UAV resources. The second priority is given to minimizing the number of required UAVs. Compared to the total average UAV path loss, the limitation on the number of UAVs constitutes a significantly more dominant practical challenge. UAVs are costly to deploy and operationally demanding, and hence, reducing N^{UAV} directly improves system feasibility. For this reason, among all solutions that achieve the same HAPS–RIS coverage level, the framework prioritizes

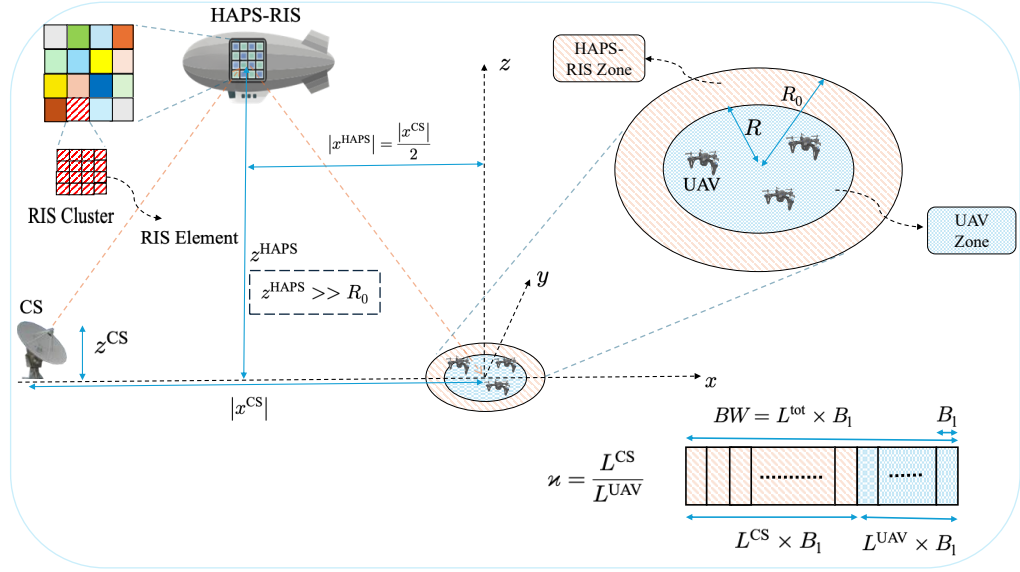


Fig. 5.3 The proposed geometric model of **OP 4**

those that require fewer UAVs, even if the corresponding UAV path loss is slightly higher. Finally, the third objective minimizes the average UAV path loss upper bound. Overall, this lexicographic ordering reflects the practical deployment logic of the system: first maximize the benefit provided by the HAPS-RIS, then minimize the dependence on the limited UAV numbers, and subsequently refine the UAV communication performance. The output of the Pareto block for each value of $\varkappa$ is passed to the convergence check, and if the criterion is not met, the bandwidth portioning factor is updated accordingly. This iterative process continues until the convergence condition is satisfied. Thus, the solution of OP 4 emerges from an iterative two-layer procedure: an outer loop that adjusts the coupling variable $\varkappa$, and an inner Pareto-based lexicographic optimizer that resolves the prioritized objectives for each $\varkappa$.

Corollary 5.1: Through the principled sequence of analytical transformations in *Theorem 5.1* and *Lemma 5.1* and the proposed mapping technique in *Proposition 5.1*, the intractable optimization problem **OP 1** is relaxed and mapped into a tractable optimization problem, **OP 4**. The proposed geometric model of **OP 4** is depicted in Fig. 5.3. In *Theorem 5.1*, k -means clustering is exploited to minimize the upper bound of (5.10), and hence **OP 1** can be relaxed into **OP 2**. In *Lemma 5.1*, a practical closed-form RIS phase-shift design is exploited to relax **OP 2** into **OP 3**. Finally, **OP 3** is mapped into **OP 4** via *RIS clustering*, *BW portioning*, and *zone association*.

The Proposed Dynamic Pareto Optimization Method: Solving OP 4

s1: Initialize $t = 0$, $\delta = 50$, $\delta' = 1$, $N^{\text{UAV},(0)}$, $R^* = R_0$, and define the set $\mathcal{I} = \{i | \sqrt{x_i^2 + y_i^2} \leq R_0\}$. Initialize index $q = 1$, maximum iteration $Q_{\max}$, define the discrete bandwidth portioning set $\varkappa = \{1, 1.5, 2, 2.5, \dots\}$ where $\varkappa^{(q)} = \varkappa[q]$.

s2: **while** $q < Q_{\max}$ **do**

s3: *Maximizing* $\tilde{U}^{\text{HAPS}}$

s3-I: **for** $t = 1$ to T **do**

s3-II: Define the set $\mathcal{B}^{(t)} = \{i' | \sqrt{x_{i'}^2 + y_{i'}^2} \leq R^{(t)}\}$ where $R^{(t)} = R_0 - t\delta$. T is the upper limit of the iteration count. Define the set $\mathcal{C}^{(t)} = \mathcal{I} - \mathcal{B}^{(t)}$ where the users in this area are supported by HAPS-RIS, and then calculate the number of the RIS elements per each cluster as $\left\lfloor \frac{M}{|\mathcal{C}^{(t)}|} \right\rfloor$.

s3-III: Map $|\mathcal{C}^{(t)}|$ clusters of RIS elements to $|\mathcal{C}^{(t)}|$ users based on a random injective function. Allocate $L_{\text{cluster}}^{(t)} = \lfloor \frac{L^{\text{CS}}}{|\mathcal{C}^{(t)}|} \rfloor$ subcarriers to each RIS cluster. Then, uniformly allocate $L_{\text{cluster}}^{(t)}$ subcarriers to $\left\lfloor \frac{M}{|\mathcal{C}^{(t)}|} \right\rfloor$ RIS elements for each RIS cluster and calculate $\rho(R^{(t)})$.

s3-IV: **While** $r_i^{\text{CS}}(\rho(R^{(t)})) \geq r_0^{\text{user}}, \forall i \in \mathcal{C}$ and the HAPS-RIS zone constraints are met and $t < T$, set $R^* = R^{(t)}$. Set $t = t + 1$.

s3-V: **end for**

s4: *Minimizing* N^{UAV} *while minimizing* $\Lambda^{\text{UAV},\text{upp}}$

s4-I: Define the set $\mathcal{B}^* = \{i' | \sqrt{x_{i'}^2 + y_{i'}^2} \leq R^*\}$ where R^* is obtained in S3.

s4-II: **for** $t' = 1$ to T' **do**

s4-III: Obtain $\mathbf{x}(N^{\text{UAV},(t')})$, $\mathbf{y}(N^{\text{UAV},(t')})$, and the user association part of $\tilde{\rho}(N^{\text{UAV},(t')})$ based on the k -means clustering method for the users as members of the set $\mathcal{B}^*$, where $N^{\text{UAV},(t')} = N^{\text{UAV},(0)} - (t' - 1)\delta'$. Apply orthogonality check for subcarriers based on the constraint $\sum_i \tilde{\rho}_{ij}' \leq 1 \forall i, j$. Then calculate $\tilde{\rho}(N^{\text{UAV},(t')})$.

s4-IV: **While** $t' < T'$ and $r_i^{\text{UAV}}(\tilde{\rho}(N^{\text{UAV},(t')}), \mathbf{x}(N^{\text{UAV},(t')}), \mathbf{y}(N^{\text{UAV},(t')})) \geq r_0^{\text{user}}, \forall i \in \mathcal{B}$ and the UAV zone related constraints are met, set $N^* = N^{\text{UAV},(t')}$. Set $t' = t' + 1$.

s4-V: **end for**

s5: **if** $|N^{\text{UAV},(q+1)} - N^{\text{UAV},(q)}| < \varepsilon$ and $|\tilde{U}^{\text{HAPS},(q+1)} - \tilde{U}^{\text{HAPS},(q)}| < \varepsilon$ **then break; else** set $q \leftarrow q + 1$.

s6: The solution of **OP 4** is obtained.

The solution of **OP 4** can be obtained via the proposed dynamic Pareto optimization technique where the building blocks and the interfaces are illustrated in Fig. 5.4.

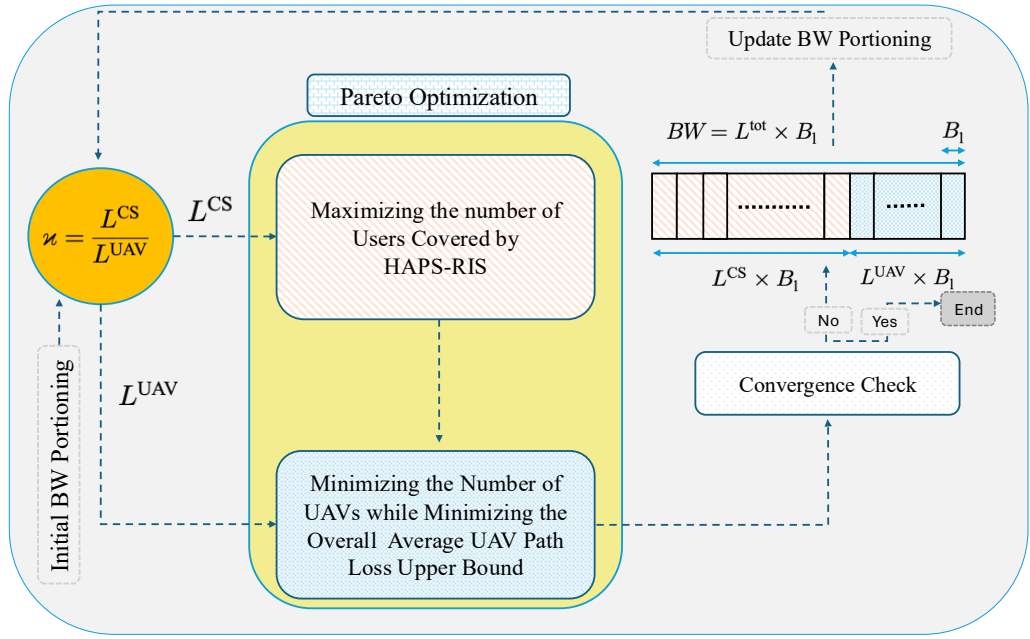


Fig. 5.4 The proposed dynamic Pareto optimization method to solve **OP 4**

5.5 Complexity and Convergence Analysis

In this section, We prove the low computational complexity and guaranteed convergence of the proposed dynamic Pareto optimization method, which are critical for ensuring scalable and reliable deployment.

5.5.1 Computational Complexity

In the proposed dynamic Pareto optimization technique, for each candidate value of the bandwidth portioning factor κ , up to $Q_{\max}$ candidates, the method executes two main blocks. Each operation represents a constant-cost algorithmic task whose execution complexity is independent of the system size and is therefore treated as $\mathcal{O}(1)$. For a fixed κ , the HAPS-RIS block performs at most T updates of the UAV-zone radius. In the worst case, each update involves partitioning all users into HAPS-RIS and UAV zones, which requires $\mathcal{O}(I)$ operations; forming RIS clusters and mapping them to HAPS-RIS users, incurring $\mathcal{O}(I)$ operations; allocating CS subcarriers and RIS elements across clusters, with $\mathcal{O}(L^{CS}(\kappa) + M)$ operations; and verifying rate and feasibility constraints for all HAPS-RIS users with $\mathcal{O}(I)$ operations. Consequently, the worst-case computational complexity per update scales as $\mathcal{O}(I + L^{CS}(\kappa) + M)$,

yielding a computational complexity for the HAPS–RIS block as

$$\mathcal{O}(T(I + L^{\text{CS}}(\boldsymbol{\kappa}) + M)). \quad (5.20)$$

The UAV block performs at most T' UAV-reduction steps. In the worst case, each step clusters all UAV-zone users using the k -means algorithm to update UAV locations and user associations. Since the clustering processes all I users across the initial $N_{\text{UAV}}^{(0)}$ UAVs and requires at most T_k internal iterations, its complexity scales as $\mathcal{O}(IN_{\text{UAV}}^{(0)}T_k)$. In addition, each step verifies rate and feasibility constraints for UAV-served users over $L^{\text{UAV}}(\boldsymbol{\kappa})$ subcarriers, contributing an extra $\mathcal{O}(IN_{\text{UAV}}^{(0)}L^{\text{UAV}}(\boldsymbol{\kappa}))$ operations. Combining these two components and accounting for T' reduction steps yields a computational complexity for the UAV block as

$$\mathcal{O}\left(T'IN_{\text{UAV}}^{(0)}(T_k + L^{\text{UAV}}(\boldsymbol{\kappa}))\right). \quad (5.21)$$

To obtain the worst-case overall computational complexity, We apply the following bounds: (i) the subcarrier counts satisfy $L^{\text{CS}}(\boldsymbol{\kappa}) \leq L^{\text{tot}}$ and $L^{\text{UAV}}(\boldsymbol{\kappa}) \leq L^{\text{tot}}$ for all tested values of $\boldsymbol{\kappa}$; (ii) the number of users in each zone is bounded by $|B| \leq I$ and $|C| \leq I$; (iii) the number of UAVs during the reduction steps satisfies $N_{\text{UAV}}^{(t')} \leq N_{\text{UAV}}^{(0)}$; and (iv) the algorithmic iteration limits T , T' , T_k , and Q_{max} are finite. Accordingly, the overall computational complexity can be obtained as

$$\mathcal{O}\left(Q_{\text{max}}[T(I + L^{\text{tot}} + M) + T'IN_{\text{UAV}}^{(0)}(T_k + L^{\text{tot}})]\right). \quad (5.22)$$

All loops are bounded and every operation grows only polynomially with the system dimensions. Therefore, the proposed solution is a low-complexity and scalable approach.

5.5.2 Convergence Analysis

For a fixed value of $\boldsymbol{\kappa}$, the proposed method first scans the UAV-zone radius as $R(t) = R_0 - t\delta$, for $t = 1, \dots, T$, over a finite discrete grid. This scan is finite and sequence $\{R(t)\}$ is decreasing monotonically which enlarges the HAPS–RIS user set. Consequently, the HAPS coverage metric $\tilde{U}^{\text{HAPS}}$ is monotonically non-decreasing along the scan. The algorithm stores the smallest radius that satisfies the HAPS–RIS feasibility constraints, which maximizes $\tilde{U}^{\text{HAPS}}$ over the tested radius grid. Given this

radius, the proposed technique then scans the number of UAVs as

$$N_{\text{UAV}}^{(t')} = N_{\text{UAV}}^{(0)} - (t' - 1)\delta', \quad \forall t' \in \{1, \dots, T'\}. \quad (5.23)$$

This scan is also finite and monotonic. The smallest UAV count that satisfies the UAV-zone constraints is retained, yielding the minimum feasible N_{UAV} . For each tested UAV count, the k -means-based UAV placement monotonically decreases a bounded objective and therefore terminates in finite time. Finally, the outer loop evaluates $\varkappa$ over the finite set and is capped by Q_{max} . Hence, the algorithm explores only a finite number of candidate solutions and necessarily terminates. Since updates are accepted only when the corresponding feasibility conditions are satisfied, the final output is feasible for **OP 4**. In summary, the proposed method implements a dynamic lexicographic Pareto search over finite grids, which guarantees convergence.

5.6 Case Study and Numerical Analysis

The numerical analysis are organized around three case studies. First, We consider a *UAV-free case study*, which arises as a *degenerate case* of **OP 4** by setting $N_{\text{UAV}} = 0$ and $\varkappa = 1$. Under this configuration, the HAPS-RIS operates as a standalone tier, utilizing 50 MHz bandwidth without any UAV assistance. Second, We consider a *UAV in action but separate spectrum case study* that arises as a disjoint degenerate case of **OP 4** by setting $\varkappa = 1$. In this case, HAPS-RIS and UAVs operate in parallel with disjoint and dedicated bandwidths of 50 MHz each, enabling the evaluation of their inherent performance trade-offs. Finally, We investigate the *UAV in action with shared spectrum case study* in which the full formulation of **OP 4** is activated. In this case, the entire 100 MHz bandwidth is treated as a shared resource and adaptively partitioned between the HAPS-RIS and UAV systems. For the proposed unified joint case study, to benchmark the framework and to highlight the impact of bandwidth coupling, We evaluate the system performance under four representative bandwidth allocation regimes. All schemes are characterized through the bandwidth portioning factor $\varkappa$, which enables a unified interpretation of the baseline strategies as special operating points of the proposed model. When $\varkappa_0 = \varkappa \rightarrow 0$, almost the entire available bandwidth is allocated to the UAVs, i.e., $L_{\text{UAV}} \gg L_{\text{CS}}$. In this regime, the contribution of the HAPS-RIS becomes negligible, and the system effectively operates as a *UAV-only* network. When $\varkappa_1 = \varkappa \rightarrow \infty$, nearly all bandwidth is assigned to the HAPS-RIS system, i.e., $L_{\text{CS}} \gg L_{\text{UAV}}$. This configuration corresponds

to the *HAPS-RIS-only* baseline. Between these two limiting cases, the operating point $\varkappa = 1$ represents an *equal bandwidth allocation* baseline, where the total bandwidth is evenly divided between the HAPS-RIS and UAV infrastructures. Although this strategy enables simultaneous utilization of both technologies, it cannot fully exploit the complementary capabilities of the two aerial systems. Finally, $\varkappa = \varkappa^{\text{opt}}$ denotes the operating point obtained via the proposed *dynamic Pareto optimization framework*. This optimized regime captures the best trade-off between the HAPS-RIS and UAV infrastructures and serves as the primary benchmark for evaluating the performance gains of the proposed joint design over all baseline schemes. It should be noted that the number of RIS elements is not an optimisation variable, but a system design parameter evaluated under different deployment scenarios and QoS requirements. Consequently, there is no universal optimal RIS size. For each deployment scenario, the appropriate RIS size is identified as the configuration that maximises the number of users served by the HAPS-RIS platform, subject to the minimum rate requirements.

In the simulations, the parameters of the HAPS-RIS system are selected based on established channel models and system assumptions reported in [28, 64], while the UAV-related parameters follow the settings adopted in [14, 84]. This choice ensures a realistic and consistent evaluation of the proposed framework. We consider $I = 20$ ground users uniformly distributed, with a minimum separation distance of $D_0 = 100$ m among them, within a circular area of radius $R_0 = 500$ m centered at $(x_0, y_0, z_0) = (0, 0, 0)$. The CS is located at $(x^{\text{CS}}, y^{\text{CS}}, z^{\text{CS}}) = (-10000, 0, 1000)$, and the HAPS platform is positioned at $(x^{\text{HAPS}}, y^{\text{HAPS}}, z^{\text{HAPS}}) = (-5000, 100, 20000)$, in Cartesian coordinate system. As elaborated in Section 5.2, the HAPS-RIS channel is modeled as a cascaded CS-RIS-user link dominated by LoS propagation, while the UAV channel follows an air-to-ground propagation model where the channel gain depends on the average path loss including LoS and NLoS probabilities. The CS employs a directional antenna with gain $G^{\text{CS}} = 43.2$ dB, while the antennas at the user terminals and UAVs are assumed to be omnidirectional with gains $G_i = 0$ dB and $G_j = 0$ dB, respectively. Unless otherwise stated, the CS transmit power is fixed at 40 dBm, while each UAV transmits with a power of 20 dBm. The path loss exponent is $\alpha = 2$, and the excessive path loss coefficients for LoS and NLoS links are $\eta_1 = 1$ and $\eta_2 = 31$, respectively. The environment-dependent constants are chosen as $\psi = 5$ and $\beta = 0.5$. In the benchmarking analysis, We interpret the baseline strategies as specific operating points within the proposed model. The system operates at a carrier frequency of $f_c = 2$ GHz and utilizes $L = 64$ orthogonal subcarriers. Each RIS element

is assumed to have unit reflection efficiency, i.e., $\mu_m = 1$ for all m . The noise power spectral density is set to $N_0 = -174$ dBm/Hz.

5.6.1 UAV-free Case Study: A Degenerate Case of OP 4

We consider a UAV-free case study, obtained as a degenerate case of **OP 4** by setting $N_{\text{UAV}} = 0$ and $\varkappa = 1$, in which the HAPS-RIS operates as a standalone tier using a dedicated 50 MHz bandwidth without UAV assistance. Fig. 5.5 and Fig. 5.6 show the percentage of users covered by the HAPS-RIS versus the number of RIS elements under different rate requirements, considering a HAPS-RIS-only deployment. In the low-rate regime, near-full coverage is achieved with a relatively small number of RIS elements. In contrast, in the high-rate regime, coverage improves more gradually and requires a substantially larger RIS surface to satisfy the increased SNR requirements. Fig. 5.7 and Fig. 5.8 illustrate the percentage of users covered by the HAPS-RIS as a function of the CS transmit power under different rate requirements. In the low-rate regime, high coverage is achieved even at moderate transmit power levels, indicating that the HAPS-RIS can efficiently satisfy modest rate demands with limited CS power. In contrast, in the high-rate regime, coverage becomes strongly power-limited, and a substantial increase in CS transmit power is required.

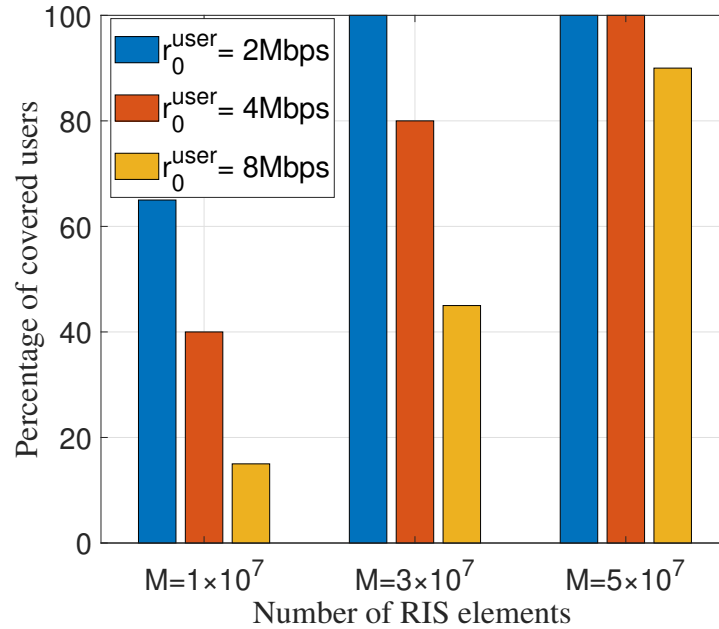


Fig. 5.5 Percentage of covered users by HAPS-RIS versus number of RIS elements in the high-rate regime for the UAV-free case with the CS transmit power of 40 dBm.

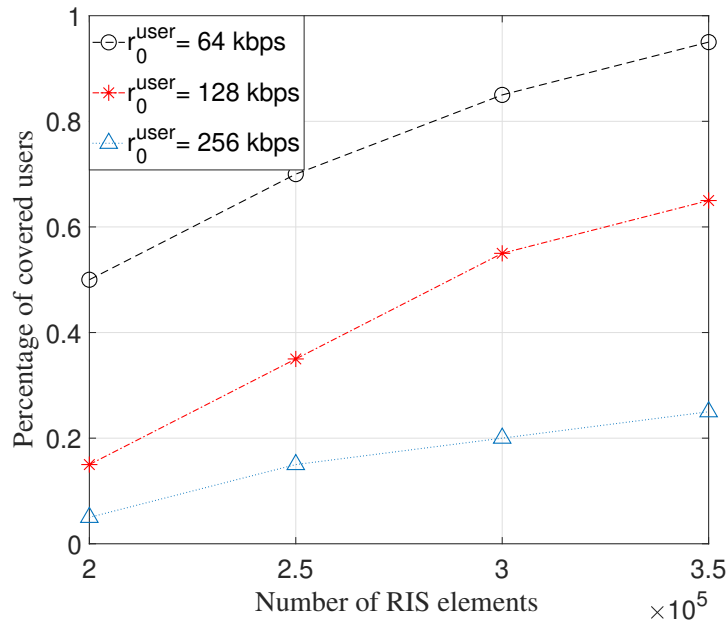


Fig. 5.6 Percentage of covered users by HAPS-RIS versus number of RIS elements in the low-rate regime for the UAV-free case with the CS transmit power of 40 dBm.

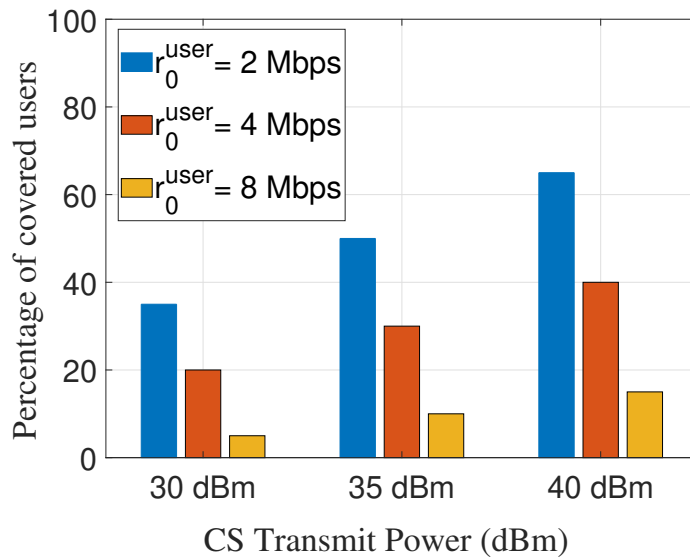


Fig. 5.7 Percentage of covered users by HAPS-RIS versus CS transmit power in the high-rate regime with 10^7 RIS elements for the UAV-free case.

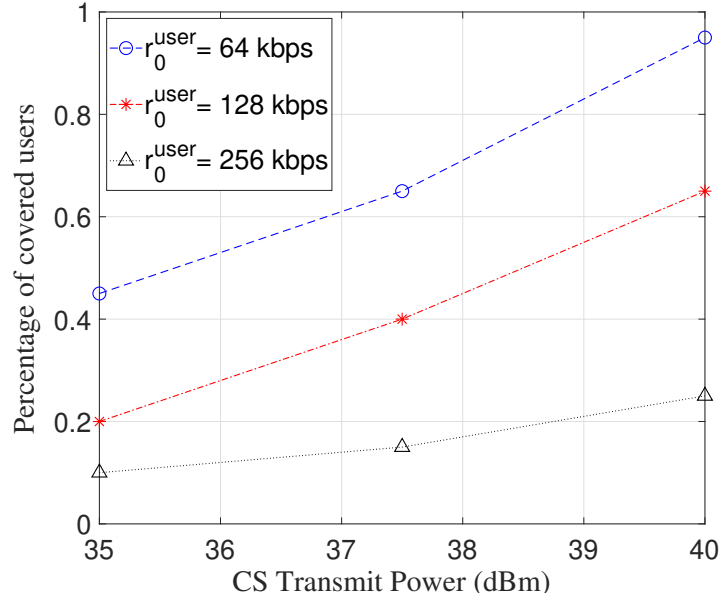


Fig. 5.8 Percentage of covered users by HAPS-RIS versus CS transmit power in the low-rate regime with 3.5×10^5 RIS elements for the UAV-free case.

5.6.2 UAV in Action but Separate Spectrum Case Study: A Disjoint Degenerate Case of OP 4

In this case, We consider a UAV-assisted case study with separate spectrum allocation, which arises as a disjoint degenerate case of **OP 4** by fixing $\varkappa = 1$. In this configuration, the HAPS-RIS and UAV tiers operate in parallel over dedicated 50 MHz bandwidths, enabling an assessment of their inherent performance trade-offs. Fig. 5.9 illustrates an example of this scenario through the zone-based association and UAV clustering mechanism. The coverage area is partitioned by a zone boundary into two distinct regions: an outer HAPS-RIS zone, where users are served by the HAPS-RIS system, and an inner UAV zone, where users are supported by UAVs. This spatial separation enables the two infrastructures to operate simultaneously while serving different subsets of users without interference. Within the UAV zone, users are further grouped into clusters based on the k -means clustering approach, with each cluster being served by a dedicated UAV positioned at the corresponding cluster centroid. Fig. 5.10 depicts the minimum number of RIS elements required to achieve full coverage over a wide range of user rate requirements, spanning from low-rate to high-rate regimes. In the low-rate regime, exploiting a single UAV leads to a significant reduction in the required RIS size. In contrast, as the rate requirement increases, the performance gap between the HAPS-RIS-only and UAV-assisted cases progressively narrows. Notably,

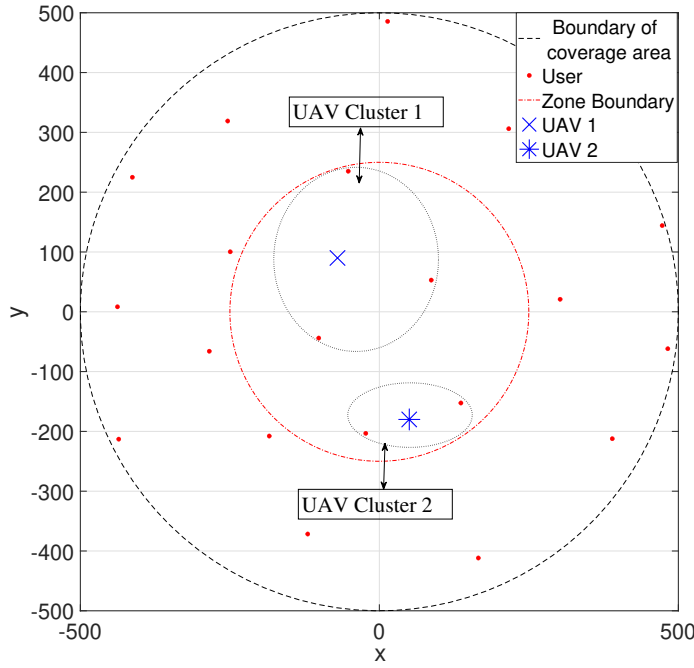


Fig. 5.9 An example of user association illustrating the coexistence of HAPS-RIS and UAVs via zone-based association and UAV clustering.

in the high-rate regime, particularly for rate requirements exceeding 4 Mbps, the assistance provided by a single UAV becomes marginal, and deploying multiple UAVs is necessary to substantially reduce the required number of RIS elements and provide the full coverage.

Fig. 5.11 and Fig. 5.12 depict the required number of UAVs as a function of the total number of RIS elements in both high- and low-rate regimes. In the high-rate regime, the number of UAVs decreases in a stepwise fashion as M increases, indicating that larger RIS sizes can progressively replace UAVs; however, this replacement typically requires RIS sizes on a much larger scale than in the low-rate case. In the low-rate regime, full coverage can be achieved with few UAVs even for moderate RIS sizes, and UAVs are eliminated with comparatively smaller increases in M , i.e., the number of RIS elements. This demonstrates a rate-dependent trade-off between RIS scale and UAV density.

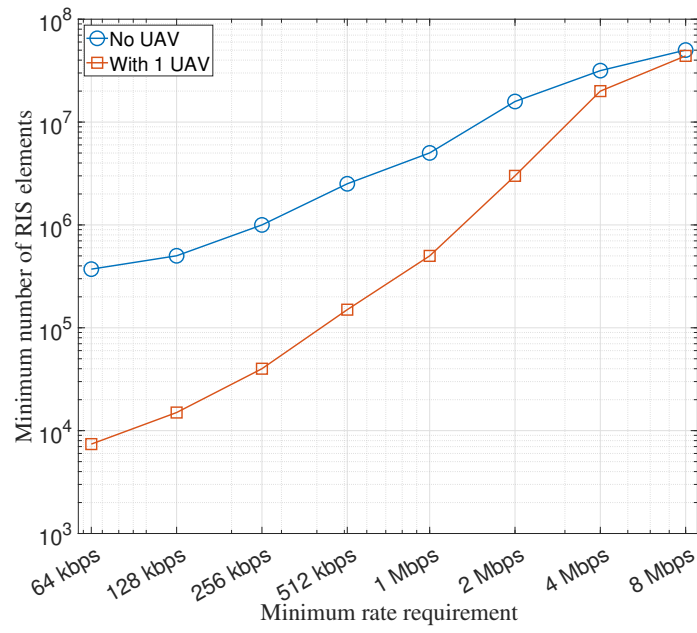


Fig. 5.10 Minimum Required number of total RIS elements versus the wide range of rate requirements to provide full coverage.

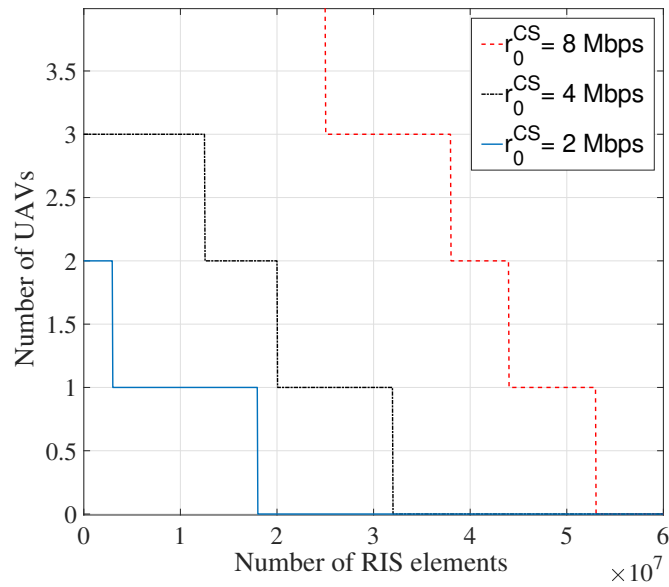


Fig. 5.11 Trade-off between the minimum required number of UAVs and the number of RIS elements to provide full coverage in the high-rate regime.

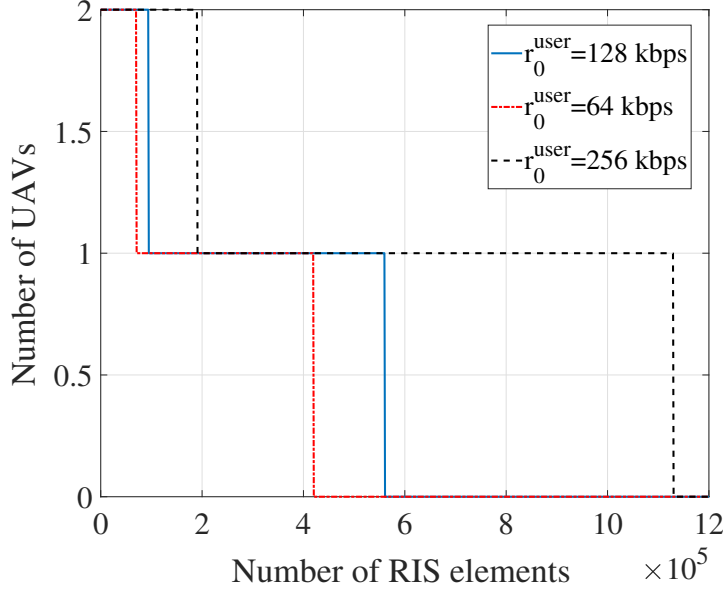


Fig. 5.12 Trade-off between the minimum required number of UAVs and the number of RIS elements to provide full coverage in the low-rate regime.

5.6.3 UAV in Action with Shared Spectrum: Unified Joint Case Study and Comparison with its Baselines

In this case study, We investigate the shared-spectrum UAV-assisted case study, in which the full formulation of **OP 4** is activated and the entire 100 MHz bandwidth is jointly and adaptively partitioned between the HAPS-RIS and UAVs. The system performance is benchmarked across four representative bandwidth regimes, all characterized by the bandwidth portioning factor $\varkappa$. The limiting cases $\varkappa \rightarrow 0$ and $\varkappa \rightarrow \infty$ recover the *UAV-only* and *HAPS-RIS-only* baselines, respectively, while $\varkappa = 1$ corresponds to equal spectrum sharing. The operating point $\varkappa = \varkappa^{\text{opt}}$, obtained via the proposed dynamic Pareto optimization, captures the optimized bandwidth portioning factor.

Fig. 5.13 and Fig. 5.14 compare the proposed unified joint solution of **OP 4**, $\varkappa = \varkappa^{\text{opt}}$, with the other baselines which can be obtained by special cases of **OP 4** by setting $\varkappa \rightarrow 0$, $\varkappa = 1$, and $\varkappa \rightarrow \infty$. In the UAV-only case, where $\varkappa = \varkappa_0$, almost the entire bandwidth is allocated to the UAVs, leaving no resources for the HAPS-RIS and resulting in zero HAPS-RIS user coverage. The equal bandwidth allocation baseline, $\varkappa = 1$, enables partial HAPS-RIS utilization; however, its performance is insufficient for high-rate demands. Allocating the whole bandwidth to the HAPS-RIS, $\varkappa = \varkappa_1$, improves HAPS-RIS coverage; however, it leads to outage in a case where users that

cannot be supported by the HAPS-RIS. This is due to the high altitude of HAPS-RIS which can affect the path loss and rate. Finally, the proposed optimized allocation, where $\varkappa = \varkappa^{\text{opt}}$, the bandwidth portioning factor is optimized by the proposed dynamic Pareto optimization technique. The optimized bandwidth allocation $\varkappa^{\text{opt}}$ significantly improves the number of users covered by the HAPS-RIS compared to equal bandwidth allocation, while preserving the flexibility to allocate the remaining bandwidth to the UAVs. This regime enables the system to prioritize HAPS-RIS coverage without exhausting all resources while retaining the ability to serve any users left uncovered through UAV assistance and ultimately support full network coverage. A direct comparison between the couple Fig. 5.5 and Fig. 5.6 and the couple Fig. 5.13 and Fig. 5.14 is meaningful only under matched RIS configurations. Specifically, the high-rate results are comparable when $M = 10^7$, while the low-rate results correspond to $M = 3.5 \times 10^5$. Under these aligned conditions, Fig. 5.13 and Fig. 5.14 exhibit a higher percentage of covered users than Fig. 5.5 and Fig. 5.6. In Fig. 5.5 and Fig. 5.6, the HAPS-RIS operates with a dedicated bandwidth of 50 MHz, whereas Fig. 5.13 and Fig. 5.14 considers a shared bandwidth scenario in which, at $\varkappa = \varkappa_1$, the entire 100 MHz bandwidth is allocated to the HAPS-RIS setup. Consequently, the increased bandwidth availability significantly enhances HAPS-RIS user coverage. Hence, the higher coverage observed in Fig. 5.13 and Fig. 5.14 are direct outcomes of bandwidth expansion.

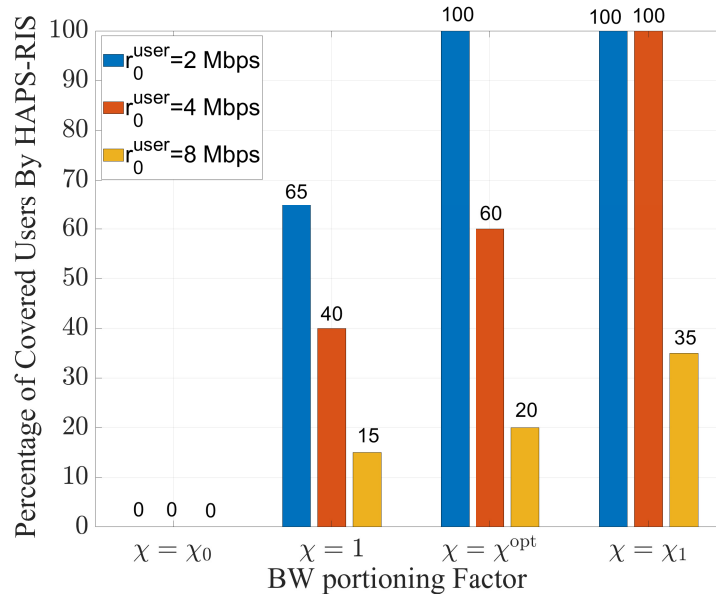


Fig. 5.13 Percentage of covered users by HAPS-RIS versus bandwidth portioning factor in the high-rate regime, where 10^7 RIS elements are exploited.

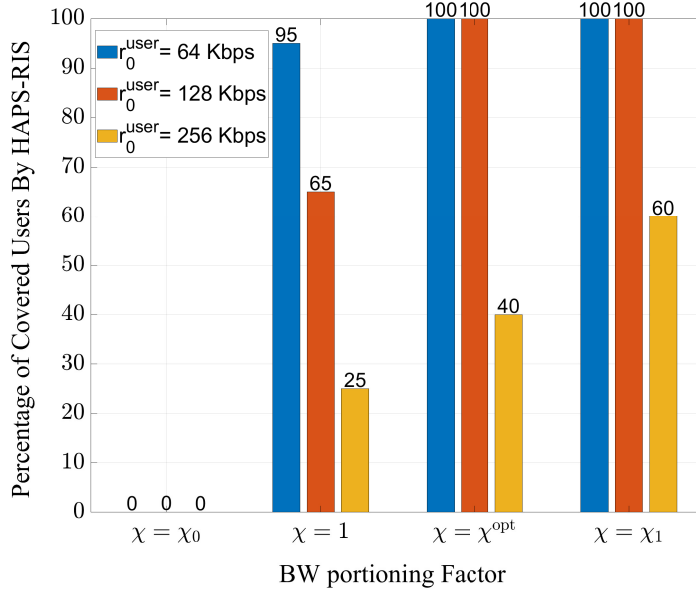


Fig. 5.14 Percentage of covered users by HAPS-RIS versus bandwidth portioning factor in the low-rate regime, where 3.5×10^5 RIS elements are exploited.

Fig. 5.15 and Fig. 5.16 illustrate the required number of UAVs under different bandwidth allocation regimes, revealing distinct behaviors in the low-rate and high-rate regimes. In both the high-rate and low-rate regimes, the optimized bandwidth allocation, $\varkappa = \varkappa^{\text{opt}}$, requires a number of UAVs that is always less than or equal to that of the equal bandwidth allocation baseline, $\varkappa = 1$. This behavior follows directly from the lexicographic Pareto design depicted in Fig. 5.4, where maximizing HAPS-RIS user coverage is assigned the highest priority, while UAV reduction is pursued whenever feasible. In the high-rate regime, although the UAV demand increases for all schemes due to stricter rate requirements, the optimized allocation consistently maintains a UAV count that does not exceed that of the equal-allocation baseline, demonstrating a more efficient balance between HAPS-RIS coverage and UAV utilization. In the extreme case $\varkappa = \varkappa_1$, almost the entire bandwidth is allocated to the HAPS-RIS, effectively eliminating the need for the UAV tier from a resource perspective and resulting in zero required UAVs. Finally, as observed in the couple Fig. 5.13 and Fig. 5.14 and the couple Fig. 5.15 and Fig. 5.16, the optimized allocation achieves a better balance between HAPS-RIS user coverage and UAV utilization than the equal bandwidth allocation in both rate regimes. In the proposed framework, the original three-objective formulation in **OP 1** is relaxed to **OP 4**, which optimizes only two objectives, while the total average UAV path loss is handled indirectly by minimizing a tractable upper bound derived through the proposed *Theorem 5.1*. This

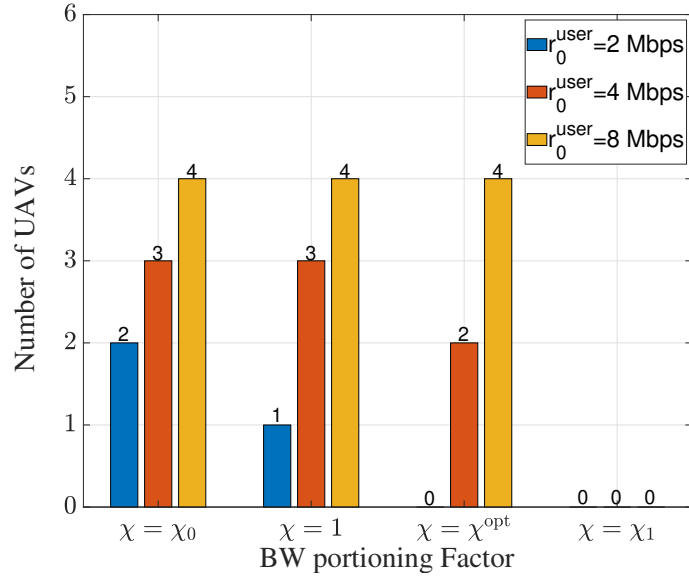


Fig. 5.15 Minimum required number of UAVs versus bandwidth portioning factor in the high-rate regime with 10^7 RIS elements.

upper bound remains well controlled across all schemes. In the worst case, the total average UAV path loss is bounded by approximately 108 dB.

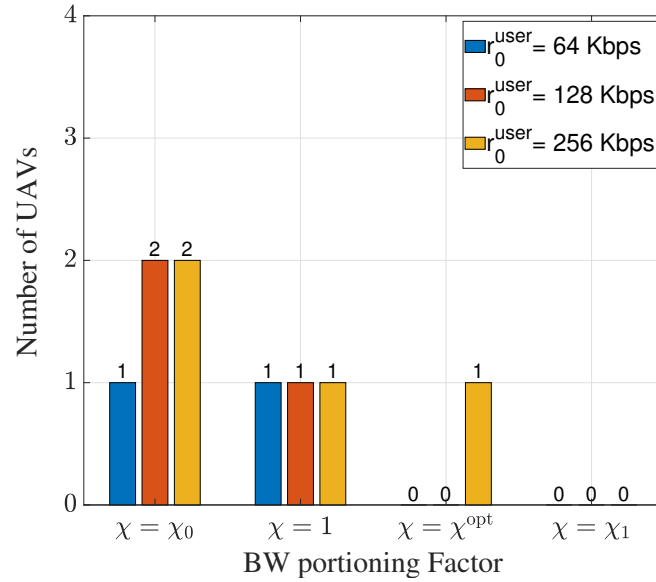


Fig. 5.16 Minimum required number of UAVs versus bandwidth portioning factor in the low-rate regime with 3.5×10^5 RIS elements.

5.7 Lessons Learned and Conclusion

This chapter culminated the architectural journey of the thesis by moving beyond mobility-aware link design, proposed in Chapter 3, and hierarchical multi-tier coordination, proposed in Chapter 4, toward a fully unified joint multi-objective framework. While Chapter 3 demonstrated how structure can tame mobility and Chapter 4 revealed that how coordination can alleviate infrastructure scarcity, this chapter removed the remaining boundaries between tiers and design variables. A novel unified multi-objective joint framework was proposed to optimize the number of users covered by HAPS-RIS, the required number of UAVs, and the total average UAV pathloss. A central technical achievement of this chapter lies in transforming an intractable large-scale optimization problem into a scalable and implementable solution. The deployment of UAVs is shown to admit an equivalence to k-means clustering, RIS phase shifts admit a simple closed-form design, and high-dimensional combinatorial association variables collapse into intuitive geometric and bandwidth-level control parameters. The proposed dynamic Pareto optimization framework further exposes the intrinsic priority structure of integrated aerial networks. It was evident that fully exploiting HAPS-RIS resources before activating UAV resources is not merely a heuristic choice, but a structurally optimal strategy. The simulations uncovered clear regime-dependent behaviors, indispensable trades-offs, benchmarking, and design guidelines. HAPS-RIS alone sufficed for low-rate services, whereas UAV assistance became progressively necessary as rate requirements increase. Remarkably, conventional architectures naturally emerged as special and degenerate cases of the unified framework, under study in this chapter, through a single bandwidth-portioning factor. This demonstrated that the proposed framework generalizes the existing architectures.

The main lesson learned in this chapter is that jointly optimizing the HAPS-RIS and UAV resources provides greater flexibility than optimizing each component independently. The results reveal a clear trade-off between the RIS size and the number of deployed UAVs, where increasing the RIS dimensions can reduce the required number of UAVs, while additional UAVs can compensate for a smaller RIS. These findings demonstrate that the performance and scalability of HAPS-RIS and UAV networks depend on the coordinated optimisation of deployment, coverage, communication resources, and spectrum allocation, rather than simply increasing the available infrastructure. The next chapter summarizes the main findings of this thesis and discusses promising directions for future research.

Chapter 6

Conclusions and Future Works

In this chapter, the core insights of the thesis, the lessons learned and the future research directions are presented. This thesis set out to rethink wireless network architectures via multi-objective vision. Rather than optimizing individual components in isolation, this thesis investigated how enabling technologies, e.g., RIS and NTN, explore the space of feasible architectures.

6.1 The Core Insights of My Thesis

The central insight of this thesis is that enabling technologies can redefine wireless network architecture by expanding the design space. In this expanded space, multi-objective optimization is not a tool for performance improvement, but a mechanism for navigating fundamentally conflicting design choices.

6.1.1 From Mobility to Controllability

At the link level, Chapter 3 establishes that mobility can be elevated from a source of uncertainty to a controllable architectural dimension. By exploiting the predictable trajectory of an aerodynamic HAPS, the time-varying cascaded channel is modeled geometrically at the level of individual RIS elements, enabling explicit characterization of Doppler spread, delay spread, and channel gain as deterministic functions of platform motion. This modeling perspective allows the RIS phase configuration to be derived in closed form, transforming what is typically a high-dimensional optimization problem into a tractable and implementable design. Beyond its analytical tractability, this framework fundamentally alters how time variation is treated in RIS-assisted systems. Instead of adapting to instantaneous channel realizations, the system anticipates the

channel evolution and proactively configures the propagation environment. This leads to a unified multi-objective control over key performance metrics that are traditionally conflicting. In particular, the proposed design enables simultaneous maximization of channel gain while suppressing Doppler spread and constraining delay spread within acceptable bounds. The numerical results in Chapter 3 validate these insights and quantify the benefits of the proposed approach. Compared to conventional static or heuristically configured RIS schemes, the mobility-aware design achieves a significant improvement in effective channel gain while reducing Doppler-induced impairments. For instance, the proposed framework demonstrates that Doppler spread can be effectively mitigated to near-zero levels under practical trajectories, while maintaining a substantial gain enhancement. Similarly, the delay spread upper bound is tightly controlled, ensuring reliable communication despite platform motion. These results highlight that the mobility of the HAPS, when properly modeled and exploited, does not degrade performance but instead becomes a resource that can be leveraged to improve it. From an architectural perspective, this contribution provides a key insight that time variation, often treated as a limitation in wireless systems, can be systematically integrated into the design space as a controllable variable. This expands the set of feasible system configurations and introduces new trade-offs that must be navigated through multi-objective optimization.

6.1.2 From Scarcity to Coordination

At the infrastructure level, Chapter 4 reframes UAV scarcity not as a fixed limitation, but as a controllable outcome of architectural design. Instead of scaling the number of UAVs to meet coverage and rate requirements, a hierarchical HAPS–RIS–assisted architecture is introduced in which the service region is structurally partitioned into heterogeneous zones. In this architecture, the HAPS–RIS layer is prioritized to serve a maximized subset of users, while UAVs are deployed only to satisfy the residual demand that cannot be supported by the passive layer. This architectural shift is formalized through a hierarchical bilevel optimization framework. At the upper level, the system determines the zone boundary and configures the RIS to maximize the number of users served by HAPS–RIS under rate constraints. At the lower level, the UAV layer adapts to this decision by minimizing the number of required UAVs while ensuring QoS requirements for the remaining users. This design captures the coupling between passive and active infrastructure, transforming user association and resource allocation into architectural decisions rather than purely local optimizations. The

results presented in Chapter 4 validate this perspective and quantify the resulting trade-offs. In particular, it is shown that increasing the number of RIS elements significantly expands the HAPS–RIS coverage region, leading to a substantial reduction in the required number of UAVs. From an architectural perspective, this contribution reveals a fundamental insight that the infrastructure scarcity is not an inherent limitation, but a variable that can be reshaped through coordination across network layers. The interaction between RIS scale and UAV deployment introduces a new class of trade-offs, where passive and active resources form a unified design space. Navigating this space requires multi-objective optimization, as improving one dimension directly impacts others.

6.1.3 From Coordination to Coupling

At the system level, Chapter 5 completes the architectural evolution of the thesis by removing the separation between network components and treating the system as a fully coupled entity. While the hierarchical design in Chapter 4 coordinates interactions across layers, it still preserves a level of structural separation between deployment, association, and resource allocation. In contrast, Chapter 5 demonstrates that these dimensions are intrinsically interdependent and must be jointly designed within a unified framework. To capture this interdependence, a comprehensive joint multi-objective optimization framework is formulated in which UAV deployment, user association, clustering, resource allocation, and RIS configuration are optimized simultaneously. This formulation reveals that passive and active infrastructures form a unified resource pool, whose interactions determine the achievable system performance. However, the resulting problem is inherently high-dimensional and combinatorial, making direct optimization intractable. A key contribution of this chapter lies in uncovering the hidden structure of this problem and exploiting it to achieve tractability. In particular, a theoretical link between classical optimization and unsupervised learning is established, showing that minimizing the upper bound of the total average UAV path loss is equivalent to a clustering operation. This insight enables the transformation of the deployment and association problem into a structured clustering task, significantly reducing computational complexity. In parallel, geometry-driven formulations yield closed-form RIS phase designs, and a mapping technique reduces the combinatorial association space into a low-dimensional representation defined by zone boundaries and bandwidth partitioning. As a result, the original NP-hard problem is reformulated in terms of a small set of dominant

architectural variables. This transformation reveals that system behavior is governed by a limited number of coupling parameters, among which the bandwidth partitioning factor plays a central role. This parameter captures the interaction between HAPS–RIS and UAV layers by controlling how spectral resources are distributed across infrastructures, effectively determining the operational regime of the network. The resulting problem is solved using a dynamic Pareto optimization approach, which adapts the priority of objectives based on the network state rather than imposing fixed weights. The simulation results in Chapter 5 validate the effectiveness of the proposed framework and provide key system-level insights. It is shown that the network exhibits regime-dependent behavior. For low data rate requirements, the HAPS–RIS layer alone is sufficient to support all users, eliminating the need for UAV deployment. As the rate requirements increase, UAVs are progressively introduced, highlighting a smooth transition between infrastructure regimes rather than a fixed deployment strategy. Furthermore, a clear and quantifiable trade-off is observed between RIS scale and UAV density, where increasing the number of RIS elements significantly reduces the number of required UAVs while maintaining QoS constraints. Compared to baseline approaches with decoupled design, the proposed unified framework achieves superior performance in terms of user coverage, UAV reduction, and path loss minimization. From an architectural perspective, this contribution establishes a fundamental insight that the complexity of next-generation wireless networks arises not from individual technologies, but from their coupling. By revealing and structuring this coupling through theory and multi-objective optimization, the design space becomes both tractable and interpretable. This shifts the role of optimization from solving isolated subproblems to governing the interaction between system components, ultimately enabling principled design of fully integrated non-terrestrial networks.

6.2 The Lessons Learned

Beyond the technical contributions, several broader lessons emerge from this thesis. (i) Geometry plays a central role in enabling tractable system design. By exploiting predictable motion and scale separation, complex and high-dimensional problems can be transformed into structured and interpretable formulations. (ii) Multi-objective design is inherent to next-generation wireless systems. The coexistence of conflicting objectives cannot be eliminated, and simplifying the problem into a single objective inevitably hides critical trade-offs. (iii) Passive and active network components form a unified resource pool. The demonstrated trade-off between RIS scale and UAV

count shows that architectural elements can be optimized jointly as interchangeable resources. (iv) Tractability is achieved through principled simplification rather than computational excess. Reducing the problem to meaningful variables is more effective than increasing computational complexity. (v) Architectural design precedes algorithmic optimization. The structure of the network determines the achievable performance region, while optimization only selects operating points within that region. Taken together, these lessons suggest a shift in perspective. The wireless network architectures should be redesigned as programmable multi-layer multi-objective frameworks whose behavior emerges from controlled interactions between their components.

6.3 Limitations

The three technical contributions of this thesis are developed under focused modelling assumptions to keep the proposed frameworks analytically tractable. Nevertheless, several practical aspects remain beyond the scope of this work. Chapter 3 assumes ideal atmospheric conditions and therefore does not account for atmospheric propagation impairments. Chapter 4 focuses on access-network resource allocation, while backhaul constraints, UAV power consumption, and exact three-dimensional UAV positioning remain beyond its scope. Chapter 5 extends the framework through joint optimization; however, backhaul-aware and fully heterogeneous scenarios are not considered. Addressing these aspects represents an important direction for moving the proposed frameworks towards 6G non-terrestrial networks.

6.4 Future Research Directions

Despite the advances presented in this thesis, several important research directions remain open.

6.4.1 ISAC

ISAC fundamentally challenges one of the implicit assumptions in this thesis that the environment is either known or can be abstracted into controllable parameters. By merging sensing and communication, the network is no longer a passive entity operating within a predefined environment, but an active system that constructs its own understanding of that environment. In such a setting, RIS configurations, UAV trajectories, and bandwidth allocations do not only optimize traditional metrics

like throughput or coverage, but also determine what the network is capable of observing and learning. The key research gap lies in the absence of an architectural framework where knowledge itself is treated as an optimization objective. This creates a deeper coupling between perception and performance, where improving communication efficiency may degrade environmental awareness, and vice versa. As a result, the design space extends beyond performance optimization into a dual domain of action and perception, transforming the network into a cognitive system that continuously redefines its interaction with the physical world.

6.4.2 SAGIN

SAGIN extend the architectural vision beyond the air-ground interface into a multi-layered system that includes satellite communication. This extension introduces a scale that is not only larger but fundamentally different in nature. Latency becomes a function of orbital dynamics, coverage is influenced by satellite trajectories, and resource allocation must operate across vastly different spatial and temporal scales. The research gap is not simply the integration of these layers, but the absence of a unified abstraction capable of capturing their interdependencies. In such systems, decisions made at one layer propagate across others, creating complex couplings that challenge conventional design approaches. The architectural design space becomes non-uniform and globally interconnected, where local optimizations may lead to unintended global inefficiencies. This requires a shift from localized optimization toward coordinated, large-scale design strategies that treat the network as a single, integrated entity operating across planetary dimensions.

6.4.3 Physical layer security

Physical layer security introduces an adversarial dimension that fundamentally alters the nature of the architectural problem. The systems considered in this thesis largely assume cooperative environments, where resources are allocated to maximize collective performance. However, in the presence of eavesdroppers and jammers, the environment becomes hostile, and architectural components such as RIS, UAVs, and HAPS must be leveraged not only for performance but also for defense. The research gap lies in the lack of frameworks where security is embedded as a core design objective rather than an additional constraint. This transforms the optimization problem into a strategic interaction, where decisions must anticipate and counteract adversarial behavior. RIS can be used to manipulate propagation environments in favor of legitimate users

while degrading the channels of attackers, and UAV mobility can be exploited to dynamically adapt to threats. The design space becomes dynamic and contested, and optimality is no longer static but dependent on the evolving actions of adversaries.

6.4.4 Self-Evolving Network Architectures

The architectural frameworks developed in this thesis assume a design-then-optimize approach, where the network structure is defined and subsequently optimized. A deeper and more fundamental direction is to allow the architecture itself to evolve over time, adapting not only its parameters but also its structure. In this context, the network becomes a dynamic system that continuously reconfigures its topology, resource allocation, and functional roles in response to environmental changes and long-term objectives. RIS, UAVs, and HAPS are no longer static components under centralized control, but active elements participating in a process of structural adaptation. The research gap lies in establishing principles that govern such evolution, including stability, convergence, and adaptability under uncertainty. This direction introduces a shift from static optimality to dynamic optimality, where the objective is not to identify a single optimal configuration, but to sustain a sequence of improving architectures over time. Such systems would require new theoretical tools that combine optimization, learning, and dynamical systems theory to enable controlled architectural evolution.

6.4.5 Digital Twin Technology

Digital twin technology introduces a paradigm shift in how wireless network architectures are modeled and optimized. Instead of relying on static or slowly updated models, a digital twin provides a real-time, continuously evolving representation of the network. This enables a transition from reactive to predictive and self-adaptive systems. The research gap lies in integrating digital twin frameworks into the core of multi-objective architectural design, rather than treating them as external tools. In this new paradigm, decisions are informed not only by the current state of the system but also by predicted future states. RIS configurations, UAV trajectories, and resource allocations can be evaluated within the digital twin before being implemented in reality, effectively allowing the network to simulate and refine its evolution. This introduces new challenges related to model accuracy, synchronization, and computational overhead, but also enables a form of recursive optimization where the network continuously redesigns itself. The architecture thus evolves into a self-referential system that anticipates, evaluates, and adapts its own future configurations.

6.4.6 Architecture as a Continuous Field

Current wireless architectures are fundamentally discrete, relying on nodes, links, and predefined topological structures. The developments in this thesis, particularly through RIS and aerial platforms, begin to blur these boundaries by introducing spatially distributed control over propagation. A natural extension of this idea is to move beyond discrete representations and treat the network as a continuous spatial field. In such a paradigm, topology is no longer defined solely by node placement, but by the spatial distribution of controllable variables such as electromagnetic response, energy density, and information flow. RIS elements, HAPS platforms, and UAVs collectively contribute to shaping a continuous communication medium rather than forming isolated components. The research gap lies in the absence of mathematical and computational frameworks capable of modeling and optimizing such continuous architectures. Addressing this challenge requires new abstractions, potentially inspired by field theory or continuum mechanics, where network behavior emerges from spatial interactions rather than discrete connections. This would fundamentally redefine wireless network design, shifting it from graph-based optimization toward the control of spatially distributed communication fields.

6.4.7 Towards Practical Deployment

Beyond the research directions discussed in this chapter, several practical challenges must also be addressed before the proposed networks can be widely deployed. Future work should investigate safe and regulation-compliant UAV deployment, including flight safety, collision avoidance, airspace regulations, and reliable operation under adverse weather conditions. In addition, practical RIS-assisted communications will require RIS-capable user equipment, together with appropriate signalling protocols and hardware support to enable efficient interaction between users and programmable wireless environments. Addressing these practical challenges is essential for translating the proposed frameworks into deployable 6G non-terrestrial networks.

6.5 Closing Remarks

This thesis demonstrates that redesigning wireless networks is fundamentally an architectural problem. Enabling technologies expand the range of possible designs, while multi-objective frameworks determine how these possibilities are structured and realized. The study in this thesis reveals a principle that the performance of

future wireless networks will be determined not by individual components, but by how effectively their interactions are designed and controlled. By treating RIS and NTN as elements of a controllable design space, this thesis contributes toward a new perspective in wireless communications, where the goal is not only to optimize networks, but to effectively redesigning them.

References

- [1] C.-X. Wang, X. You, X. Gao, X. Zhu, Z. Li, C. Zhang, H. Wang, Y. Huang, Y. Chen, H. Haas *et al.*, “On the road to 6g: Visions, requirements, key technologies, and testbeds,” *IEEE Communications Surveys & Tutorials*, vol. 25, no. 2, pp. 905–974, 2023.
- [2] Z. Zhang, Y. Xiao, Z. Ma, M. Xiao, Z. Ding, X. Lei, G. K. Karagiannidis, and P. Fan, “6g wireless networks: Vision, requirements, architecture, and key technologies,” *IEEE vehicular technology magazine*, vol. 14, no. 3, pp. 28–41, 2019.
- [3] H. Tataria, M. Shafi, A. F. Molisch, M. Dohler, H. Sjöland, and F. Tufvesson, “6g wireless systems: Vision, requirements, challenges, insights, and opportunities,” *Proceedings of the IEEE*, vol. 109, no. 7, pp. 1166–1199, 2021.
- [4] W. Saad, M. Bennis, and M. Chen, “A vision of 6g wireless systems: Applications, trends, technologies, and open research problems,” *IEEE network*, vol. 34, no. 3, pp. 134–142, 2019.
- [5] G. Liu, Y. Huang, N. Li, J. Dong, J. Jin, Q. Wang, and N. Li, “Vision, requirements and network architecture of 6g mobile network beyond 2030,” *China Communications*, vol. 17, no. 9, pp. 92–104, 2020.
- [6] J. Cui, S. X. Ng, D. Liu, J. Zhang, A. Nallanathan, and L. Hanzo, “Multiobjective optimization for integrated ground-air-space networks: Current research and future challenges,” *IEEE Vehicular Technology Magazine*, vol. 16, no. 3, pp. 88–98, 2021.
- [7] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, “Drone small cells in the clouds: Design, deployment and performance analysis,” in *2015 IEEE global communications conference (GLOBECOM)*. IEEE, 2015, pp. 1–6.
- [8] —, “Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage,” *IEEE Communications Letters*, vol. 20, no. 8, pp. 1647–1650, 2016.
- [9] —, “Mobile internet of things: Can uavs provide an energy-efficient mobile architecture?” in *2016 IEEE global communications conference (GLOBECOM)*. IEEE, 2016, pp. 1–6.
- [10] —, “Mobile unmanned aerial vehicles (uavs) for energy-efficient internet of things communications,” *IEEE Transactions on Wireless Communications*, vol. 16, no. 11, pp. 7574–7589, 2017.

- [11] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 3, pp. 2334–2360, 2019.
- [12] M. Mozaffari, X. Lin, and S. Hayes, "Toward 6g with connected sky: Uavs and beyond," *IEEE Communications Magazine*, vol. 59, no. 12, pp. 74–80, 2022.
- [13] W. Saad, M. Bennis, M. Mozaffari, and X. Lin, *Wireless communications and networking for unmanned aerial vehicles*. Cambridge University Press, 2020.
- [14] A. Azizi, S. Parsaeefard, M. R. Javan, N. Mokari, and H. Yanikomeroglu, "Profit maximization in 5G+ networks with heterogeneous aerial and ground base stations," *IEEE Transactions on Mobile Computing*, vol. 19, no. 10, pp. 2445–2460, 2019.
- [15] A. Azizi and N. Mokari, "Joint resource allocation, 3D placement, and user association in ABS-supported IoT networks considering adaptive modulation technique," *Transactions on Emerging Telecommunications Technologies*, vol. 30, no. 12, p. e3632, 2019.
- [16] Y. Liu, X. Liu, X. Mu, T. Hou, J. Xu, M. Di Renzo, and N. Al-Dhahir, "Reconfigurable intelligent surfaces: Principles and opportunities," *IEEE communications surveys & tutorials*, vol. 23, no. 3, pp. 1546–1577, 2021.
- [17] M. Di Renzo, A. Zappone, M. Debbah, M.-S. Alouini, C. Yuen, J. De Rosny, and S. Tretjakov, "Smart radio environments empowered by reconfigurable intelligent surfaces: How it works, state of research, and the road ahead," *IEEE journal on selected areas in communications*, vol. 38, no. 11, pp. 2450–2525, 2020.
- [18] M. Di Renzo, K. Ntontin, J. Song, F. H. Danufane, X. Qian, F. Lazarakis, J. De Rosny, D.-T. Phan-Huy, O. Simeone, R. Zhang *et al.*, "Reconfigurable intelligent surfaces vs. relaying: Differences, similarities, and performance comparison," *IEEE Open Journal of the Communications Society*, vol. 1, pp. 798–807, 2020.
- [19] C. Pan, H. Ren, K. Wang, J. F. Kolb, M. El Kashlan, M. Chen, M. Di Renzo, Y. Hao, J. Wang, A. L. Swindlehurst *et al.*, "Reconfigurable intelligent surfaces for 6g systems: Principles, applications, and research directions," *IEEE Communications Magazine*, vol. 59, no. 6, pp. 14–20, 2021.
- [20] W. Tang, M. Z. Chen, X. Chen, J. Y. Dai, Y. Han, M. Di Renzo, Y. Zeng, S. Jin, Q. Cheng, and T. J. Cui, "Wireless communications with reconfigurable intelligent surface: Path loss modeling and experimental measurement," *IEEE transactions on wireless communications*, vol. 20, no. 1, pp. 421–439, 2020.
- [21] J. Ye, J. Qiao, A. Kammoun, and M.-S. Alouini, "Non-terrestrial communications assisted by reconfigurable intelligent surfaces," *Proceedings of the IEEE*, vol. 110, no. 9, pp. 1423–1465, 2022.
- [22] T. C. Tozer and D. Grace, "High-altitude platforms for wireless communications," *Electronics & communication engineering journal*, vol. 13, no. 3, pp. 127–137, 2001.

- [23] S. Chandrasekharan, K. Gomez, A. Al-Hourani, S. Kandeepan, T. Rasheed, L. Goratti, L. Reynaud, D. Grace, I. Bucaille, T. Wirth *et al.*, “Designing and implementing future aerial communication networks,” *IEEE communications magazine*, vol. 54, no. 5, pp. 26–34, 2016.
- [24] J. Qiu, D. Grace, G. Ding, M. D. Zakaria, and Q. Wu, “Air-ground heterogeneous networks for 5g and beyond via integrating high and low altitude platforms,” *IEEE Wireless Communications*, vol. 26, no. 6, pp. 140–148, 2019.
- [25] S. C. Arum, D. Grace, and P. D. Mitchell, “A review of wireless communication using high-altitude platforms for extended coverage and capacity,” *Computer Communications*, vol. 157, pp. 232–256, 2020.
- [26] D. Grace, J. Thornton, G. Chen, G. P. White, and T. C. Tozer, “Improving the system capacity of broadband services using multiple high-altitude platforms,” *IEEE Transactions on Wireless Communications*, vol. 4, no. 2, pp. 700–709, 2005.
- [27] G. K. Kurt *et al.*, “A vision and framework for the high altitude platform station (HAPS) networks of the future,” *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 729–779, 2021.
- [28] S. Alfattani, W. Jaafar, Y. Hmamouche, H. Yanikomeroglu, and A. Yongaçoglu, “Link budget analysis for reconfigurable smart surfaces in aerial platforms,” *IEEE Open Journal of the Communications Society*, vol. 2, pp. 1980–1995, 2021.
- [29] A. Azizi and A. Farhang, “RIS meets aerodynamic HAPS: A multi-objective optimization approach,” *IEEE Wireless Communications Letters*, vol. 12, no. 11, pp. 1851–1855, 2023.
- [30] A. Azizi, M. A. Kishk, and A. Farhang, “Exploring the impact of HAPS-RIS on UAV-based networks: A novel network architecture,” in *Proceedings of the 2025 IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. IEEE, 2025, pp. 1–7.
- [31] A. Azizi, M. R. Ghourtani, M. A. Kishk, H. Ahmadi, and A. Farhang, “HAPS-RIS and UAV integrated networks: A unified joint multi-objective framework,” *arXiv preprint arXiv:2602.09960*, 2026.
- [32] A. Azizi and A. Farhang, “Reflect from the smart sky: Ris-enabled aerodynamic haps-assisted networks,” in *Inaugural School of Engineering Research Symposium (SERS)*, p. 8.
- [33] A. Azizi, M. Kishk, and A. Farhang, “Transforming the skies: How haps-ris is shaping the future of uav networks,” in *Second School of Engineering Postgraduate Research Symposium*, p. 9.
- [34] A. Azizi and A. Farhang, “What will be the network architecture for next generation networks?” SFI ADVANCE CRT Research Colloquium, Tralee, Ireland, Apr. 2024, presented at SFI ADVANCE CRT Research Colloquium. [Online]. Available: <https://doi.org/10.5281/zenodo.13898250>

- [35] 3GPP, “Study on New Radio to support non-terrestrial networks,” 3rd Generation Partnership Project (3GPP), Tech. Rep. TR 38.811, 2020, [Online]. Available: <https://www.3gpp.org/ftp//Specs/archive>.
- [36] —, “Study on new radio to support non-terrestrial networks,” 3rd Generation Partnership Project (3GPP), Sophia Antipolis, France, Tech. Rep. TR 38.811, 2018, [Online]. Available: <https://www.3gpp.org/ftp//Specs/archive>.
- [37] P. Ramezani, B. Lyu, and A. Jamalipour, “Toward RIS-enhanced integrated terrestrial/non-terrestrial connectivity in 6G,” *IEEE Network*, vol. 37, no. 3, pp. 178–185, 2022.
- [38] D. Grace and M. Mohorcic, *Broadband communications via high altitude platforms*. John Wiley & Sons, 2011.
- [39] D. Grace, M. H. Capstick, M. Mohorcic, J. Horwath, M. B. Pallavicini, and M. Fitch, “Integrating users into the wider broadband network via high altitude platforms,” *IEEE Wireless Communications*, vol. 12, no. 5, pp. 98–105, 2005.
- [40] B. Kirsch and O. Montagnier, “Towards the advent of high-altitude pseudo-satellites (haps),” *Disruptive Technology and Defence Innovation Ecosystems*, vol. 5, pp. 181–201, 2019.
- [41] H. T. Friis, “A note on a simple transmission formula,” *Proceedings of the IRE*, vol. 34, no. 5, pp. 254–256, 1946.
- [42] A. Mohammed, A. Mehmood, F.-N. Pavlidou, and M. Mohorcic, “The role of high-altitude platforms (HAPs) in the global wireless connectivity,” *Proceedings of the IEEE*, vol. 99, no. 11, pp. 1939–1953, Nov. 2011.
- [43] “SHARP (Stationary High Altitude Relay Platform),” [Online]. Available: <http://www.friendsofcrc.ca/Projects/SHARP/sharp.html>, accessed: Aug. 01, 2023.
- [44] “AeroVironment, Inc.” [Online]. Available at <https://www.avinc.com/resources/press-releases/view/solar-high-altitude-long-endurance-uas>, accessed: Aug. 01, 2023.
- [45] “The first stratospheric UAS of its kind (Zephyr),” [Online]. Available: <https://www.airbus.com/en/products-services/defence/uas/uas-solutions/zephyr>, accessed: Aug. 01, 2023.
- [46] “Flying Aquila: Early lessons from the first full-scale test flight and the path ahead,” [Online]. Available: <https://engineering.fb.com/connectivity/flying-aquila-early-lessons-from-the-first-full-scale-test-flight-and-the-path-ahead>, accessed: Aug. 01, 2023.
- [47] “Aquila: What’s next for high-altitude connectivity?” [Online]. Available: <https://engineering.fb.com/2017/10/26/connectivity/aquila-what-s-next-for-high-altitude-connectivity/>, accessed: Aug. 01, 2023.

- [48] “Building communications networks in the stratosphere,” [Online]. Available: <https://engineering.fb.com/2015/07/30/connectivity/building-communications-networks-in-the-stratosphere/>, accessed: Aug. 01, 2023.
- [49] “HAPSMobile,” [Online]. Available: <https://www.hapsmobile.com/>, accessed: Aug. 01, 2023.
- [50] “PHASA-35,” [Online]. Available: <http://prismaticltd.co.uk/products/phasa-35/>, accessed: Aug. 01, 2023.
- [51] “PHASA-35 first flight,” [Online]. Available: <https://www.baesystems.com/en/article/ground-breaking-solar-powered-unmanned-aircraft-makes-first-flight>, accessed: Aug. 01, 2023.
- [52] E. Karapantazis and F. N. Pavlidou, “Broadband communications via high altitude platforms: A survey,” *IEEE Communications Surveys & Tutorials*, vol. 7, no. 1, pp. 2–31, 2005.
- [53] F. A. d’Oliveira, F. C. L. D. Melo, and T. C. Devezas, “High altitude platforms—present situation and technology trends,” *Journal of Aerospace Technology and Management*, vol. 8, no. 3, pp. 249–262, Jul.–Sep. 2016.
- [54] A. Aragon-Zavala, J. L. Cuevas-Ruíz, and J. A. Delgado-Penín, *High Altitude Platforms for Wireless Communications*. Hoboken, NJ, USA: Wiley, 2008.
- [55] “CAPANINA,” [Online]. Available: <https://capanina.hosted.york.ac.uk>, accessed: Aug. 01, 2023.
- [56] “StratXX,” [Online]. Available: <http://www.stratxx.com/>, accessed: Aug. 01, 2023.
- [57] “Elevate,” [Online]. Available: <http://www.zero2infinity.space/elevate/>, accessed: Aug. 01, 2023.
- [58] “Expanding internet connectivity with stratospheric balloons,” [Online]. Available: <https://x.company/projects/loon/>, accessed: Aug. 01, 2023.
- [59] “What’s up with stratobus,” [Online]. Available: <https://www.thalesgroup.com/en/worldwide/space/news/whats-stratobus>, accessed: Aug. 01, 2023.
- [60] E. Björnson, H. Wymeersch, B. Matthiesen, P. Popovski, L. Sanguinetti, and E. De Carvalho, “Reconfigurable intelligent surfaces: A signal processing perspective with wireless applications,” *IEEE Signal Processing Magazine*, vol. 39, no. 2, pp. 135–158, 2022.
- [61] Ö. Özdogan, E. Björnson, and E. G. Larsson, “Intelligent reflecting surfaces: Physics, propagation, and pathloss modeling,” *IEEE Wireless Communications Letters*, vol. 9, no. 2, pp. 581–585, May 2020.
- [62] 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. 116 753–116 773, Aug. 2019.

- [63] E. Björnson, Ö. Özdoğan, and E. G. Larsson, “Intelligent reflecting surface versus decode-and-forward: How large surfaces are needed to beat relaying?” *IEEE Wireless Communications Letters*, vol. 9, no. 2, pp. 244–248, 2020.
- [64] S. Alfattani *et al.*, “Aerial platforms with reconfigurable smart surfaces for 5G and beyond,” *IEEE Communications Magazine*, vol. 59, no. 1, pp. 96–102, 2021.
- [65] S. Alfattani, A. Yadav, H. Yanikomeroglu, and A. Yongacoglu, “Beyond-cell communications via HAPS-RIS,” in *Proceedings of the 2022 IEEE Globecom Workshops (GC Wkshps)*. IEEE, 2022, pp. 1383–1388.
- [66] S. Alfattani, A. Yadav, H. Yanikomeroglu, and A. Yongacoglu, “Resource-efficient HAPS-RIS enabled beyond-cell communications,” *IEEE Wireless Communications Letters*, vol. 12, no. 4, pp. 679–683, 2023.
- [67] K. Tekbiyik, G. K. Kurt, C. Huang, A. R. Ekti, and H. Yanikomeroglu, “Channel estimation for full-duplex RIS-assisted HAPS backhauling with graph attention networks,” in *Proceedings of the IEEE International Conference on Communications (ICC)*. IEEE, 2021, pp. 1–6.
- [68] A. M. Benaya, M. S. Hassan, M. H. Ismail, T. Landolsi, and M. I. AlHajri, “Outage analysis for a HAPS-mounted IRS-assisted multi-user communication system,” in *Proceedings of the 2024 6th International Conference on Communications, Signal Processing, and Their Applications (ICCSPA)*. IEEE, 2024, pp. 1–6.
- [69] A. M. Benaya, M. I. AlHajri, M. H. Ismail, M. S. Hassan, and T. Landolsi, “Outage analysis of THz-enabled IRS-assisted multi-user space-air-ground integrated networks,” *IEEE Open Journal of the Communications Society*, 2025.
- [70] B. Karaman, İ. Baştürk, F. Kara, M. Ozturk, S. Taşkın, and H. Yanikomeroglu, “On the trade-off between sum-rate and energy efficiency through the convergence of HAPS and active RIS technologies,” in *Proceedings of the 2025 IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. IEEE, 2025, pp. 1–6.
- [71] R. Deka, M. S. Alam, I. Ahmed, and S. Anees, “Performance analysis of a RIS-HAPS assisted FSO-UWOC system for ground-air-underwater connectivity,” in *Proceedings of the 2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall)*. IEEE, 2024, pp. 1–5.
- [72] J. Yuan, G. Chen, M. Wen, R. Tafazolli, and E. Panayirci, “Secure transmission for THz-empowered RIS-assisted non-terrestrial networks,” *IEEE Transactions on Vehicular Technology*, vol. 72, no. 5, pp. 5989–6000, 2022.
- [73] H. Memarian, S. M. Razavizadeh, and A. Kuhestani, “Enhancing physical layer security in RIS-enabled HAP communications within non-terrestrial networks,” *IEEE Access*, 2025.
- [74] H. T. Le, T. V. Nguyen, H. T. T. Pham, and N. T. Dang, “Harvested energy evaluation of free-space optics RIS-assisted ground-HAP-UAV system over composite channels,” in *Proceedings of the 2024 IEEE 99th Vehicular Technology Conference (VTC2024-Spring)*. IEEE, 2024, pp. 1–5.

- [75] E. Bjornson, E. A. Jorswieck, M. Debbah, and B. Ottersten, "Multiobjective signal processing optimization: The way to balance conflicting metrics in 5g systems," *IEEE Signal Processing Magazine*, vol. 31, no. 6, pp. 14–23, 2014.
- [76] J.-H. Cho, Y. Wang, R. Chen, K. S. Chan, and A. Swami, "A survey on modeling and optimizing multi-objective systems," *IEEE Communications Surveys & Tutorials*, vol. 19, no. 3, pp. 1867–1901, 2017.
- [77] I. Giagkiozis and P. J. Fleming, "Methods for multi-objective optimization: An analysis," *Information Sciences*, vol. 293, pp. 338–350, 2015.
- [78] K. Miettinen, *Nonlinear Multiobjective Optimization*. Boston, MA, USA: Springer, 1999.
- [79] N. Gunantara, "A review of multi-objective optimization: Methods and its applications," *Cogent Engineering*, vol. 5, no. 1, p. 1502242, 2018.
- [80] K. Deb, K. Sindhya, and J. Hakanen, "Multi-objective optimization," in *Decision sciences*. CRC Press, 2016, pp. 161–200.
- [81] B. Matthiesen, E. Björnson, E. De Carvalho, and P. Popovski, "Intelligent reflecting surface operation under predictable receiver mobility: A continuous time propagation model," *IEEE Wireless Communications Letters*, vol. 10, no. 2, pp. 216–220, 2021.
- [82] E. Björnson, E. A. Jorswieck, M. Debbah, and B. Ottersten, "Multi-objective signal processing optimization: The way to balance conflicting metrics in 5G systems," *IEEE Signal Processing Magazine*, vol. 31, no. 6, pp. 14–23, 2014.
- [83] J. G. Andrews, F. Baccelli, and R. K. Ganti, "A tractable approach to coverage and rate in cellular networks," *IEEE Transactions on Communications*, vol. 59, no. 11, pp. 3122–3134, 2011.
- [84] A. Al-Hourani, S. Kandeepan, and S. Lardner, "Optimal LAP altitude for maximum coverage," *IEEE Wireless Communications Letters*, vol. 3, no. 6, pp. 569–572, Dec. 2014.
- [85] A. K. Jain, "Data clustering: 50 years beyond K-means," *Pattern Recognition Letters*, vol. 31, no. 8, pp. 651–666, 2010.