

**JOINT BEAMFORMING OPTIMIZATION FOR
PHYSICAL LAYER SECURITY AND POWER
EFFICIENCY IN RIS-ASSISTED SYMBIOTIC
RADIO NETWORKS**

BY

MUNEEF ABDULWASA RAZAZ MOHAMMED

A Thesis Presented to the

COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

ELECTRICAL ENGINEERING

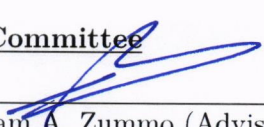
DECEMBER 2024

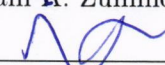
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN 31261, SAUDI ARABIA

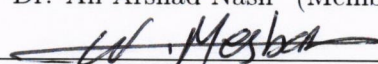
DEANSHIP OF GRADUATE STUDIES

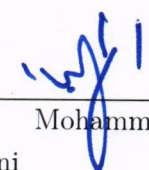
This thesis, written by **MUNEEF ABDULWASA RAZAZ MOHAMMED** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

Thesis Committee

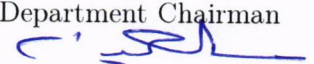

Prof. Salam A. Zummo (Adviser)


Dr. Ali Arshad Nasir (Member)


Dr. Wessam Ali Mesbah (Member)


Dr. Mohammad Al-Muhaini

Department Chairman


Prof. Suliman Al-Homidan
Dean of Graduate Studies

December 2024

Date



©Muneef Mohammed
2024

To my dear and cherished family

ACKNOWLEDGMENTS

All praise and gratitude belong to Allah, the Most Compassionate and Merciful, for His infinite blessings upon me. May peace and blessings be upon Prophet Muhammad and his family. I would like to sincerely thank my thesis advisor, Prof. Salam A. Zummo, for his continuous support, guidance, and encouragement throughout this journey, without which this work would not have been possible in its current form.

I am also deeply grateful to my thesis committee members, Dr. Ali Nasir and Dr. Wessam Mesbah, for their valuable insights, time, and efforts, which greatly contributed to improving the quality of this thesis.

My heartfelt appreciation goes to all those who supported me during this journey, both technically and morally. I am especially thankful to my friends Makarem, Bashir, Banafa'a, Ali, Fadi and Akram, for their support and companionship.

Lastly, my deepest gratitude is extended to my beloved family—my parents, my wife, and my siblings—whose constant belief in me, patience, and support have been a source of great strength and motivation. Words cannot fully capture my appreciation for their sacrifices and love. May Allah bless them abundantly.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	vi
LIST OF TABLES	ix
LIST OF FIGURES	x
LIST OF ABBREVIATIONS	xiii
ABSTRACT (ENGLISH)	xiv
ABSTRACT (ARABIC)	xvi
CHAPTER 1 INTRODUCTION	1
1.1 Theoretical Background	3
1.1.1 Symbiotic Radio (SR)	4
1.1.2 Physical Layer Security (PLS)	6
1.1.3 Communication Modes	7
1.1.4 Reconfigurable Intelligent Surface (RIS)	8
1.1.5 Channel Model	10
1.2 Literature Review	12
1.3 Thesis Contributions	16
CHAPTER 2 MULTICAST BEAMFORMING	19
2.1 Signal Model	20
2.2 CSI Uncertainty Model	24
2.2.1 Bounded CSI Error Model	25
2.2.2 Statistical CSI Error Model	25
2.3 Power Consumption	26

2.3.1	Active RIS	26
2.3.2	Passive RIS	27
2.4	Problem Formulation and Proposed Solution	27
2.4.1	Bounded CSI Error Model	27
2.4.2	Statistical CSI Error Model	38
2.4.3	Gradient Search with Randomization Method	45
2.5	Results and Discussion	48
2.6	Conclusions	56
CHAPTER 3	MULTI-USER BEAMFORMING	57
3.1	Signal Model	58
3.2	Power Consumption	62
3.2.1	Active RIS	62
3.2.2	Passive RIS	62
3.3	Problem Formulation and Proposed Solution	63
3.3.1	Bounded CSI Error Model	63
3.3.2	Statistical CSI Error Model	76
3.3.3	Gradient Search with Randomization Method for Multi-User Case	85
3.4	Results and Discussion	86
3.5	Conclusions	94
CHAPTER 4	THESIS CONCLUSIONS AND FUTURE RE- SEARCH	96
4.1	Thesis Conclusions	96
4.2	Future Research	97
REFERENCES		99
VITAE		105

LIST OF TABLES

1.1	Notational conventions	4
1.2	Channel descriptions used throughout this thesis.	11
2.1	Simulation parameters 1	49
3.1	Simulation parameters 2.	88

LIST OF FIGURES

1.1	Overview of physical layer security (PLS) attack types.	7
1.2	Communication modes.	8
1.3	The difference between active and passive RIS hardware architectures.	9
1.4	Tree diagram highlighting the area of interest in this research.	13
2.1	SR system model setup.	19
2.2	The flowchart of Algorithm 1	38
2.3	Comparison with the gradient search in Algorithm 2 with our proposed Algorithm.	48
2.4	Convergence performance of Algorithm 1.	50
2.5	Total power consumption vs uncertainty level of the direct channel to EVs-II, ξ_{h_o}	51
2.6	With SU's EVs and without power consumption vs SNR requirement to decode v , Ψ_v , with two different numbers active RIS elements (N).	52
2.7	Power consumption vs RIS elements number (N) for different active RIS amplification factors ρ^2	53
2.8	Power consumption vs SNR requirement for decoding $s(\kappa)$	54
2.9	Power consumption vs distance of the SU from RIS in meters.	55
3.1	The flowchart of Algorithm 3.	78
3.2	Comparison with the gradient search in Algorithm 4 with our proposed Algorithm.	89
3.3	Convergence performance of Algorithm 3.	90
3.4	Total power consumption vs uncertainty level of the direct channel to EVs-II, ξ_{h_o}	91

3.5	Total power consumption vs the number of RIS elements (N) for multicast and multi-user beamforming at active amplification factor $\rho^2 = 15$	92
3.6	Power consumption vs the SNR for decoding $s(\kappa)$, $\Psi_s(\kappa)$	92
3.7	Power consumption vs the distance between the SU and RIS in meters.	93
3.8	Power consumption vs SNR requirement at the SU to decode v , Ψ_v	94

LIST OF ABBREVIATIONS

6G	Sixth-Generation
AO	alternating optimization
AWGN	additive-white-gaussian-noise
CSI	channel state information
LoS	line-of-sight
PTx	primary transmitter
PU	primary user
QoS	quality of service
RIS	reconfigurable intelligent surface
SDR	Semidefinite Relaxation
SIC	successive interference cancellation
SINR	signal-to-interference noise ratio
SR	symbiotic radio
SROCR	sequential rank one constraint relaxation
SU	secondary user

THESIS ABSTRACT

NAME: Muneef Abdulwasa Razaz Mohammed

TITLE OF STUDY: Joint Beamforming Optimization for Physical Layer Security and Power Efficiency in RIS-Assisted Symbiotic Radio Networks

MAJOR FIELD: Electrical Engineering

DATE OF DEGREE: December 2024

The advent of 6G networks represents a transformative milestone in global communications, emphasizing sustainable, energy-efficient, and highly connected systems to improve quality of life. Achieving these goals necessitates addressing critical challenges in energy efficiency and spectral efficiency (SE) to support massive connectivity demands, requiring approximately 76 GHz of spectral resources.

This research investigates a joint optimization framework for transmit beamforming at the primary transmitter (PTx) and reflection beamforming at an active reconfigurable intelligent surface (RIS). The objective is to minimize total power consumption while ensuring security and quality of service (QoS) within a symbiotic radio (SR) environment. Specifically, multicast beamforming is employed to transmit a common message to primary users (PUs) via an active RIS, which simultaneously modulates its own message to a secondary user (SU).

In this setup, two types of eavesdroppers pose security threats: Type 1 targets PUs, while Type 2 targets the SU. Due to the lack of cooperation from eavesdroppers in providing channel state information (CSI), two models are considered: bounded and statistical. To address the non-convex optimization problem, an alternating optimization (AO) algorithm is proposed, decomposing the problem into two alternating subproblems.

The second phase of this thesis focuses on multi-user beamforming at the PTx, where each user receives distinct signals, introducing interference complexity. This challenge is addressed by formulating three subproblems: Firstly, optimizing beamforming vectors, secondly, refining RIS reflection beamforming, and finally updating interference thresholds. These thresholds decouple constraints into positive and negative parts, each with distinct signal-to-interference-plus-noise ratio (SINR) thresholds. The optimization framework accounts for worst-case scenarios where eavesdroppers can eliminate interference, ensuring robust system performance.

Numerical analysis highlights the efficacy of the proposed algorithms in significantly reducing total power consumption across scenarios. Active RIS outperforms passive RIS consistently, and the statistical CSI error model delivers superior performance over the bounded CSI model due to its precise representation of eavesdroppers' channels.

ملخص الرسالة

الاسم:

منيف عبدالواسع رزاز محمد

عنوان الدراسة:

تحسين التشكيل المشترك للحزم من أجل أمان الطبقة الفيزيائية وكفاءة الطاقة في الشبكات الراديوية التعاونية المدعومة

بسطح ذكي قابل لإعادة التشكيل (RIS)

التخصص:

قسم الهندسة الكهربائية

تاريخ الدرجة العلمية: أكتوبر 2024

تمثل شبكات الجيل السادس (6G) علامة فارقة وتحولاً جذرياً في مجال الاتصالات العالمية، حيث تركز على الأنظمة المستدامة والفعالة من حيث استهلاك الطاقة والمتصلة بشكل كبير لتحسين جودة الحياة. تحقيق هذه الأهداف يتطلب معالجة التحديات الحرجة المتعلقة بكفاءة الطاقة والكفاءة الطيفية (SE) لدعم الطلبات الهائلة على الاتصال، والتي تتطلب ما يقارب 76 جيجاهرتز من الموارد الطيفية. تتناول هذه الدراسة إطاراً لتحسين مشترك لتشكيل حزم الإرسال في المرسل الرئيسي (PT) وتشكيل حزم الانعكاس في السطح الذكي النشط القابل لإعادة التشكيل (RIS). يتمثل الهدف في تقليل استهلاك الطاقة الكلي مع ضمان الأمان وجودة الخدمة (QoS) ضمن بيئة الراديو التعاونية. (SR) تحديداً، يتم استخدام تشكيل الحزم للإرسال المتعدد لإرسال رسالة مشتركة إلى المستخدمين الرئيسيين (PUs) عبر السطح الذكي النشط، الذي يقوم في الوقت نفسه بتعديل رسالته الخاصة إلى مستخدم ثانوي (SU). في هذا الإطار، يشكل نوعان من المتنصتين تهديدات أمنية: النوع الأول يستهدف المستخدمين الرئيسيين (PUs) بينما يستهدف النوع الثاني المستخدم الثانوي (SU). ونظراً لعدم تعاون المتنصتين في توفير معلومات حالة القناة (CSI)، يتم اعتبار نموذجين: النموذج المحدود والنموذج الإحصائي. لمعالجة مشكلة التحسين غير المحدبة، تم اقتراح خوارزمية التحسين بالتناوب (AO) التي تقوم بتقسيم المشكلة إلى مشكلتين فرعيتين يتم حلها بالتناوب.

تتركز المرحلة الثانية من هذه الأطروحة على تشكيل الحزم متعددة المستخدمين في محطة القاعدة (BS) حيث يتلقى كل مستخدم إشارات مختلفة، مما يضيف تعقيداً ناجماً عن التداخل. يتم معالجة هذا التحدي من خلال صياغة ثلاث مشكلات فرعية: أولاً تحسين

متجهات تشكيل الحزم، ثانياً تحسين تشكيل حزم انعكاس السطح الذكي، (RIS) وثالثاً تحديث العتبات الجزئية. تعمل هذه العتبات على فصل القيود إلى أجزاء موجبة وسلبية، ولكل منها عتبات مميزة لنسبة الإشارة إلى التداخل بالإضافة إلى الضوضاء. (SINR) يأخذ إطار التحسين بعين الاعتبار أسوأ السيناريوهات حيث يمكن للمتتصتين إزالة التداخل، لضمان أداء نظام قوي.

تظهر التحليلات العددية فعالية الخوارزميات المقترحة في تقليل استهلاك الطاقة الإجمالي بشكل كبير عبر السيناريوهات المختلفة. كما يتفوق السطح الذكي النشط (Active RIS) بشكل ملحوظ على السطح الذكي السلبي (Passive RIS)، ويوفر نموذج خطأ معلومات حالة القناة الإحصائي (CSI) أداءً أفضل مقارنةً بالنموذج المحدود بفضل تمثيله الدقيق لقنوات المتتصتين.

CHAPTER 1

INTRODUCTION

The potential for transformative impact on global communication networks is evident in the emergence of Sixth-Generation (6G) networks, which aim to establish sustainable connections worldwide, ultimately enhancing the quality of life [1]. To achieve this goal, 6G networks need to be both energy and spectral-efficient (SE) to support this massive connectivity and the need for about 76 GHz spectral resources (i.e., Bandwidth) [2], [3], [4].

To face these challenges, researchers investigated using different technologies, such as cognitive radio (CR). SE can be enhanced by dynamic spectrum allocation shared between a primary user (PU) and an unlicensed secondary user (SU), which opportunistically accesses the spectrum [5]. While this approach has proved to be a promising solution, it has its cons, such as the need for detailed power information and accurate channel state information (CSI). More importantly, it needs active devices, which rely on energy-hungry components such as oscillators and up-converters, to satisfy all these working requirements which makes it not the perfect solution to solve the urgent needs of 6G networks. Moreover, CR not only requires active components for active transmission but also relies on complex

spectrum sensing techniques, which are inefficient for low-power, low-processing communication devices like IoT sensors [6], [4].

In recent years, symbiotic radio (SR) has been considered as a promising solution for the next generation of wireless networks, where it supports a mutual understanding between the primary and the secondary systems by allow them to work cooperatively. SR has excellent promise as an appropriate approach for achieving effective communication that maximizes the use of spectrum, reducing power consumption, and total cost by utilizing the primary system's infrastructure, energy, and spectrum resources to support secondary transmission without the need for continuous spectrum sensing as in CR (Refer to reference [4] for detailed comparison between CR and SR) [7].

Without the need for active components and exclusive spectrum resources, SUs can passively backscatter their own information on the primary transmission by means of load impedance variation. Thus, energy efficiency (EE) and SE can be improved through SR approach. This is a win-win relationship for both PU and SU since the SU transmission can be considered as an additional path to enhance PU's performance.

Moreover, the security considerations in the next generations of wireless networks are considered as another vital aspect of sustainable and reliable communications. While the end user quality of service (QoS) is a critical requirement in communications, securing the integrity of the information during the transmission is another important challenge. The 6G is expected to connect a massive number of devices specially low-energy devices such as sensors, thus it is challenging to implement a sophisticated security algorithms such as conventional crypto-

graphic encryption for them due to the limited processing capacity of such devices since these algorithms are working in the application layer. This is why physical layer security by means of advanced signal processing can be the best measure for such systems especially with broadcast and superposition transmissions during the downlink because of its vulnerability to security breaches [8].

Additionally, reconfigurable intelligent surface (RIS) is expected to play a potential role in the 6G due to its ability to reconfigure the channel and create more paths for the signal to reach the receiver especially if the direct link is blocked or weak [9].

Therefore, motivated by all of the above (i.e., SR, RIS, and PLS), this work aims to optimize the energy consumption of the overall system by jointly optimizing the transmit beamforming at the PTx, and the reflection beamforming vector at the RIS under QoS, and security constraints for two communication modes (i.e., Multicast and Multi-user beamforming, to be explained later in this chapter) to guarantee reliable, efficient and secure green communication systems.

In the following sections of this chapter, a brief theoretical background to provide the reader with the necessary concepts and knowledge needed for understanding the thesis work is stated, this is followed by the literature review and thesis contributions. Table 1.1 describes the notations considered throughout of this thesis.

1.1 Theoretical Background

This section gives the reader the essential knowledge and background to understand the various topics covered in this thesis. Only subjects directly related to the

Table 1.1: Notational conventions

Notation	Description
f	Scalar variables (italic letters)
$\mathbf{F}$	Matrices (bold uppercase letters)
$\mathbf{f}$	Vectors (bold lowercase letters)
$(\cdot)^H$	Conjugate transpose of a matrix or vector
$ \cdot $	Absolute value of a scalar
$\ \cdot\ _L$	L -norm of a vector
$\text{diag}(\mathbf{v})$	Diagonal matrix with elements of $\mathbf{v}$ along the diagonal
$\text{Tr}(\mathbf{A})$	Trace of matrix $\mathbf{A}$ (sum of diagonal elements)
$\mathbb{C}$	Space of complex numbers
$\mathcal{S}$	Predefined set
$\mathbb{E}[X]$	Expectation of a random variable X
$\mathcal{CN}(0, \sigma^2)$	Circularly Symmetric Complex Gaussian (CSCG) distribution with zero mean and variance σ^2

proposed work are included here.

1.1.1 Symbiotic Radio (SR)

The SR network can be differentiated into two main distinct categories; namely, Parasitic SR (PSR) in which higher data rate is transmitted by the SU and commensal SR (CSR) which is for low data rate users, contingent upon the nature of the symbol periods of both the backscatter device (BD), where the RIS is the backscatter device in this setup, and the PTx [8].

Symbiotic Radio Setups

This subsection states the main types of relationships in SR [10].

Parasitic SR: in PSR, the secondary transmission data rate is close to the data rate of the primary transmission, which causes interference between the two signals at the receiver. As a result, complex interference cancellation techniques are needed. Moreover, synchronization between all components of the SR system is required.

Commensal SR: CSR setup is suitable for low data rate internet-of-things (IoTs) devices, which, in consequence, reduces the drawbacks of the PSR in a way

the SU's signal can be considered as another path of the PTx signal and reduces the interference at the receiver. Thus, by cooperatively working in the SR network, the receiver can easily decode both signals jointly, given that the $T_{SU} = KT_{PU}$ is the symbol duration of secondary transmission, and K is the number of primary symbols compared to the secondary symbols. If K is large, the spectrum growth issue will be negligible. It is worth mentioning that CSR is used throughout this thesis work.

Main Components of SR System

Throughout this thesis, we will use the PU to denote the primary receiver of the signal in which we have multiple PUs. Similarly, SU is the receiver of secondary transmission which is receiving RIS information. In general, for any SR system, the following are the main components and may have different names [10].

The primary transmitter (PTx) constitutes the dedicated broadcasting apparatus serving as the principal communication source for a given system, encompassing modalities such as Wi-Fi, and Radar. Emitting either radio frequency (RF) or optical signals, the PTx sends these signals along communication paths (i.e., with or without RIS) to authorized end-users.

The primary receiver (PRx) , which in this thesis is denoted as the PU, functions as the designated destination of the transmitted signal from the PTx. This receiver may either exist as an independent entity solely focused on capturing the primary signal only as in this work where PUs focus on decoding their intended signals, or operates as a cooperative receiver that can decode both primary and secondary signals and in this case is called cooperative receiver (CoR).

The secondary transmitter (STx) typically encompasses IoT sensors.

These sensors utilize the transmitted signal from the PTx to convey their data to the designated receiver, i.e., SRx. In this study, STx is the active RIS which performs signal reflection and amplification as well as transmitting its confidential information to the SU.

The secondary receiver (SRx) is intended to receive the conveyed signal on the primary transmission by jointly decoding both signals utilizing the mutual cooperation offered by SR. In this study, the SU is the SRx that receives the reflected signal after being modulated and amplified by the active RIS.

1.1.2 Physical Layer Security (PLS)

PLS is a way to protect the confidentiality of the information transmission by securing transmissions directly at the signal level, reducing computational demands [11]. Security is a critical concern in modern networks, particularly for low-power devices like sensors that lack the capacity for complex encryption algorithms [12]. Moreover, 6G will bring many sensitive techniques that are very sensitive to security attacks such as the sensitivity to pilot contamination attacks in massive multiple-input-multiple-output (MIMO) and nonorthogonal multiple access (NOMA). As a result, PLS is expected to play a crucial role in the next generations. For example, optimizing the beamforming at the MIMO transmitter can enhance the security against eavesdropping [12] which aligns with the work of this thesis.

There are several types of PLS attacks as shown in Figure 1.1. Eavesdropping attackers try to capture sensitive information without authorization. As they do not send any signals, it becomes difficult for legitimate transmitters or receivers to detect or pinpoint their location. On the other hand, contaminating attackers

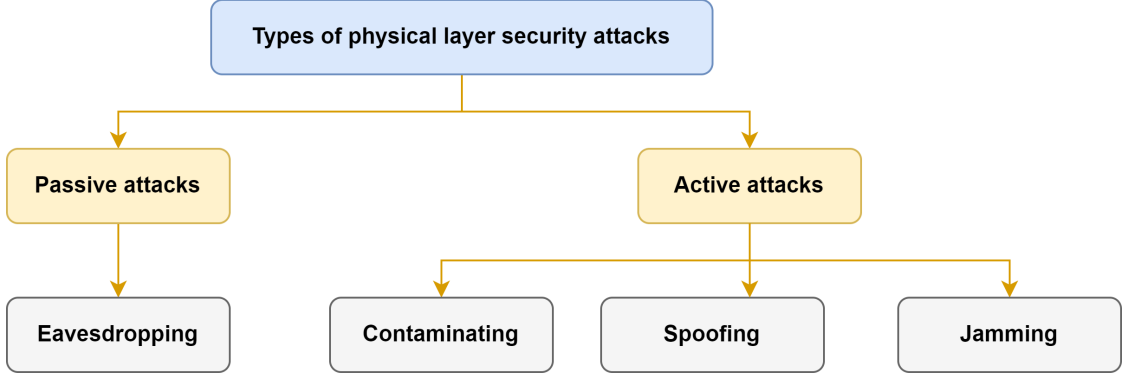


Figure 1.1: Overview of physical layer security (PLS) attack types.

seek to interfere with the channel estimation process in order to gain unauthorized benefits during the subsequent communication phase. Additionally, spoofing attackers try to infiltrate or disrupt legitimate communications by injecting falsified identity information. Finally, the goal of a jamming attacker is to disrupt legitimate communications by overwhelming the channel with noise. In this thesis, we focus on the passive type of attacks i.e., eavesdropping [12][11].

1.1.3 Communication Modes

In this subsection, the two communication modes used throughout this work will be explained.

Multicast Beamforming

Multicast Beamforming is a communication mode in which multiple antenna PTx optimizes the beams for legitimate users sending a common message to all. This can be shown in Figure 1.2 b) where the same signal $\mathbf{s}$ is transmitted while ensuring only the intended users are receiving this common message [13]

Multi-user Beamforming

Multi-user beamforming, which can be called as broadcast beamforming too, on the other hand, is used to transmit different messages for different users by means of optimizing the multiple beamforming at multiple antenna transmitter. This can be illustrated in Figure 1.2 a). The objective is to transmit each signal to its intended user to enhance transmission rate and security [14].

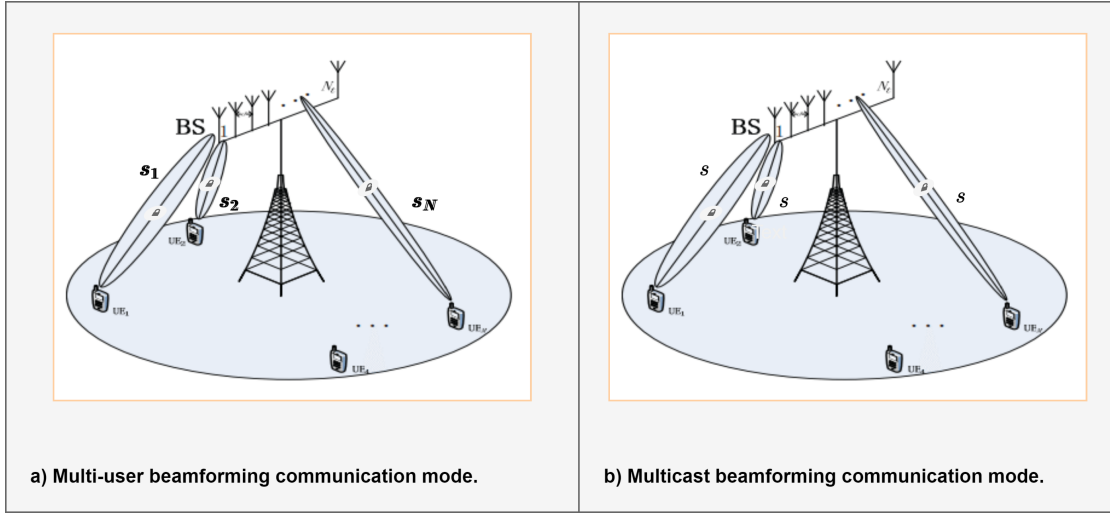


Figure 1.2: Communication modes.

1.1.4 Reconfigurable Intelligent Surface (RIS)

The active and passive RIS architectures will be introduced in this section. Figure 1.3 shows the difference in the hardware construction of both types active and passive.

Passive RIS as shown in Figure 1.3 (a), consists of many passive reflecting elements that can be controlled in order to reflect the incident signal with a controlled phase shift. This controllable feature of the phase shifts for each element can be done using the impedance-adjustable circuit. Because of the passive nature of the

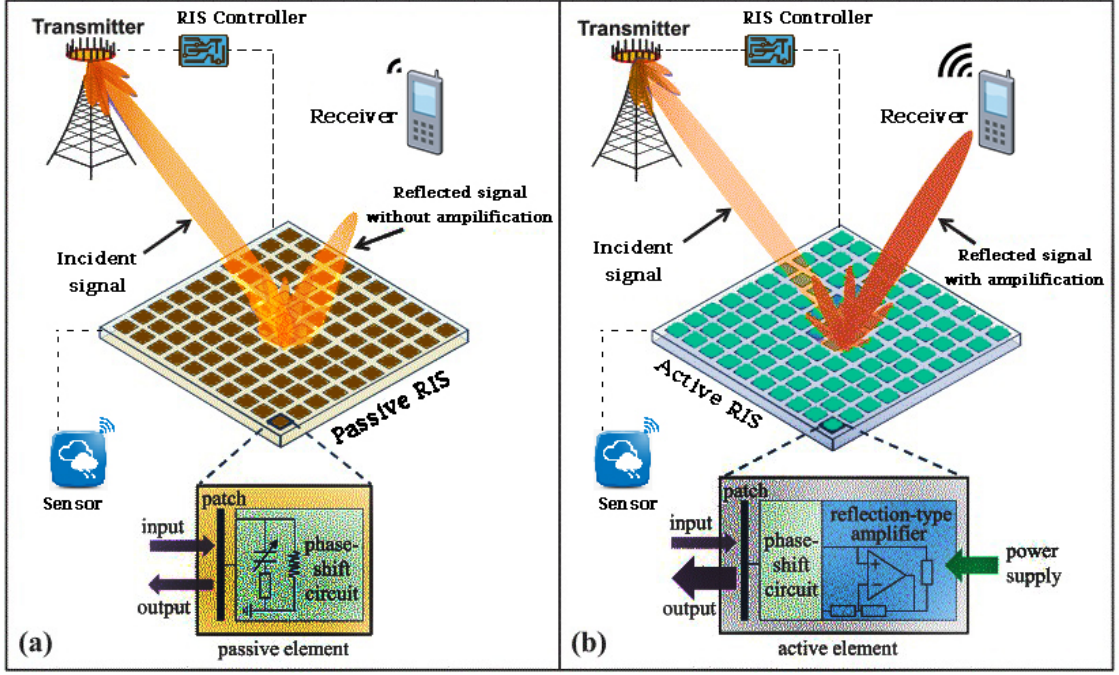


Figure 1.3: The difference between active and passive RIS hardware architectures.

passive RIS, zero direct current is consumed, with close to zero thermal noise [9].

The model describes the signal reflected by the passive RIS used mostly in the literature as follows [15]

$$\mathbf{y} = \mathbf{\Theta}\mathbf{x}, \quad (1.1)$$

where $\mathbf{x} \in \mathbb{C}^N$ represent the incident signal on the RIS, $\mathbf{\Theta} = \text{diag}(e^{j\theta_1}, \dots, e^{j\theta_N}) \in \mathbb{C}^{N \times N}$, and $\mathbf{y} \in \mathbb{C}^N$ is the reflected signal by RIS. Therefore, controlling the phases of each element will enhance the gain at the receiver by constructively adding them together which for sure would increase the received SNR. Unfortunately, there is a negative cost particularly if the direct link is not weak, which leads to what is called “multiplicative fading” effect caused by passive RIS. In other words, the path-loss effect is represented by the product of the path losses between the PT-RIS and RIS-PR links, rather than their summation. Consequently, a large number of elements is required to offset this loss.

Active RIS as shown in Figure 1.3 (b), comprises of an active reflection-type amplifier, which is built of electronic components like active converters or integrated circuits [16]. Active RIS was proposed to face the challenges caused by “multiplicative fading” [9]. Unlike passive RIS, active RIS is capable of both reflecting signals with controlled phase adjustments and amplifying the incident signal. As a result, the signal reflected from the active RIS will also include active noise, which can be represented by the following equation

$$\mathbf{y} = \mathbf{\Theta}\mathbf{x} + \mathbf{\Theta}\mathbf{n}_d + \mathbf{n}_s \quad (1.2)$$

where $\mathbf{\Theta} = \text{diag}(\rho_1 e^{j\theta_1}, \dots, \rho_N e^{j\theta_N}) \in \mathbb{C}^{N \times N}$ represent the reflection coefficient matrix of the active RIS, where $\rho_n \in R_+$ denote the amplification of the n^{th} reflection element of the active RIS where $\rho_n > 1$ due to the amplification gain. The second term (1.2) is related to the dynamic noise of the active RIS, not like the passive RIS now we cannot neglect it due to the amplification in which $\mathbf{n}_d \sim \mathcal{CN}(\mathbf{0}_N, \sigma_v^2 \mathbf{I}_N)$. The static noise is neglected as compared to $\mathbf{n}_d$.

While passive RIS merely reflects the received signal without amplification, active RIS not only reflects but also amplifies the incoming signal. On the other hand, there is a third type which is called hybrid RIS. Hybrid RIS is an integration between active and passive RIS, where some of the reflecting elements are active and others are passive.

1.1.5 Channel Model

Throughout this work, we consider a block flat-fading channel model, which means the channel remains constant for the duration of one secondary symbol [17]. The

complex baseband equivalent channels used throughout this thesis are described in Table 1.2, where N denotes the number of reflection elements of the RIS, and M denotes the number of antennas at the PT.

Table 1.2: Channel descriptions used throughout this thesis.

Channel Description	Channel Symbol	Dimensions
From PTx to RIS	$\mathbf{H}_{(P,RIS)}$	$\mathbb{C}^{N \times M}$
From PTx to j^{th} PU	$\mathbf{h}_{p,j}^H$	$\mathbb{C}^{1 \times M}$
From PTx to l^{th} EVs-I	$\mathbf{h}_{e1,l}^H$	$\mathbb{C}^{1 \times M}$
From PTx to EVs-II	$\mathbf{h}_{e2}^H$	$\mathbb{C}^{1 \times M}$
From PTx to SU	$\mathbf{h}_s^H$	$\mathbb{C}^{1 \times M}$
From RIS to j^{th} PU	$\mathbf{g}_{p,j}^H$	$\mathbb{C}^{1 \times N}$
From RIS to l^{th} EVs-I	$\mathbf{g}_{e1,l}^H$	$\mathbb{C}^{1 \times N}$
From RIS to EVs-II	$\mathbf{g}_{e2}^H$	$\mathbb{C}^{1 \times N}$
From RIS to SU	$\mathbf{g}_s^H$	$\mathbb{C}^{1 \times N}$

All RIS-associated channels are characterized by both large-scale and small-scale fading. The large-scale fading is dependent on distance and can be represented as

$$\eta(d) = \left(\frac{\lambda}{4\pi} \right)^2 d^{-\delta} \quad (1.3)$$

where λ is the wavelength at the carrier frequency, d represents the distance of the transmitter from the receiver, and δ is the path-loss exponent. The small-scale fading follows a Rician fading model for the RIS-related channels, as described in [17]. Our primary focus is on the channel between the PTx and RIS, denoted by $\mathbf{H}_{(P,RIS)}$, while the other channels can be modeled similarly.

Since the Rician model comprises both line-of-sight (LoS) and non-NLoS com-

ponents, $\mathbf{H}_{(P,RIS)}$ is modeled as

$$\mathbf{H}_{(P,RIS)} = \sqrt{\eta(d_{T,R})} \left(\sqrt{\frac{\Gamma_{T,R}}{\Gamma_{T,R} + 1}} \mathbf{H}_{(P,RIS)}^{\text{LoS}} + \sqrt{\frac{1}{\Gamma_{T,R} + 1}} \mathbf{H}_{(P,RIS)}^{\text{NLoS}} \right), \quad (1.4)$$

where $\Gamma_{T,R}$ is the Rician factor, $d_{T,R}$ is the distance between the PTx and RIS, and $\mathbf{H}_{(P,RIS)}^{\text{LoS}}$ and $\mathbf{H}_{(P,RIS)}^{\text{NLoS}}$ are the LoS and NLoS components of the channel $\mathbf{H}_{(P,RIS)}$, respectively. The NLoS component $\mathbf{H}_{(P,RIS)}^{\text{NLoS}}$ follows a complex-Gaussian distribution, $\mathbf{H}_{(P,RIS)}^{\text{NLoS}} \sim \mathcal{CN}(0, 1)$. On the other hand, the LoS component can be modeled as

$$\mathbf{H}_{P,RIS}^{\text{LoS}} = a_N(\phi^{\text{AoA}}) a_M^H(\phi^{\text{AoD}}) \quad (1.5)$$

where $a_X(\phi) = [1, e^{j\pi \sin(\phi)}, \dots, e^{j\pi(D-1) \sin(\phi)}]^T$, $D \in \{M, N\}$.

The same large-scale fading model used with the RIS-related channels will be used to model the channels unrelated to the RIS, whereas the small-scale fading is characterized by Rayleigh fading, where each component follows $\mathcal{CN}(0, 1)$ [3].

1.2 Literature Review

The literature review has been conducted in this section to identify the research gap and to give a historical overview of the previous research on SR. Fig. 1.4 shows the hierarchical architecture of the literature review in this section, highlighting our area of research.

The work on SR has been the focus of researchers recently [2]. The authors in [18], the first to introduce moving from the concept of backscatter communication

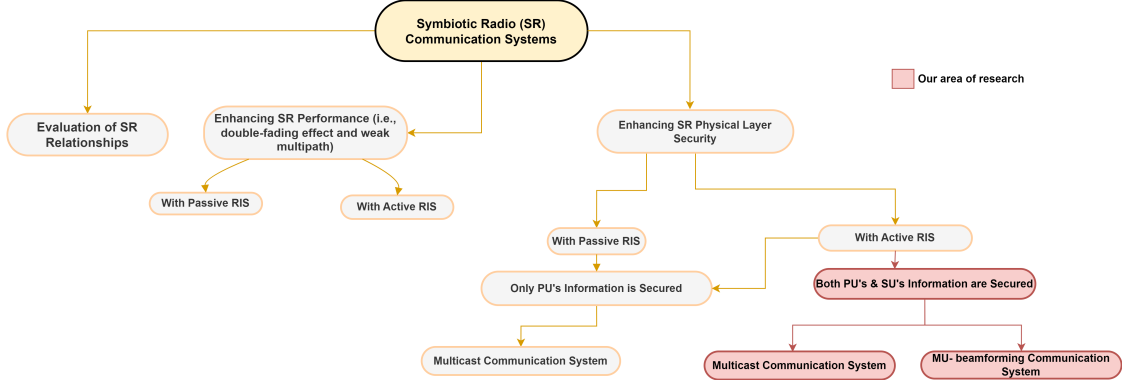


Figure 1.4: Tree diagram highlighting the area of interest in this research.

to the SR communication. In addition to introducing the concept of SR, they derived the achievable rates for both PU and SU under the different SR setups and solved a power allocation problem. In [8], the two SR configurations; namely, CSR and PSR, were analyzed with an assumption of a single PU, a single SU, and a multi-antenna PTx. For each setup, the achievable rate for both primary and secondary links is derived. The authors address maximizing the sum-rate problem by optimizing the transmit beamforming at the PTx, using the Semidefinite Relaxation (SDR) technique.

Resource allocation is another direction that has gained a potential focus from researchers recently. The primary emphasis of the paper [19] centers around balancing SE and EE in multi-SU SR systems. They introduced a coordinated approach to managing resources involving both bandwidth and power, aiming to optimize the combined weighted value of SE and EE.

Aiming to establish secure communication within SR networks, the paper [20] proposed a novel Artificial Noise assisted transmission scheme to maximize the ergodic secrecy rate of the SU while considering the QoS constraints of the primary system. This work uniquely considers a scenario where the CSI of the eavesdropper

is unknown, creating a paradigm shift in enhancing security within the existing SR systems. Aside from proposing a new transmission scheme, this study also provides analytic expressions for the achievable ergodic secrecy rate within SR systems, reducing system design and analysis complexity significantly.

All the previous works consider only SUs with a single antenna which degrades the performance of SR since the SR system suffers from the double-fading effect in the channel which affects the received signal strength. Moreover, signal antenna SU will offer only one multi-path link which makes its contribution to the enhancement of the PU link significantly weak.

To tackle these two major concerns, recently, RIS has been investigated and integrated to the wireless communications in order to enhance the performance of transmission. Due to its physical structure, RIS with a massive number of reflecting elements that can be programmed smartly to enhance the channel and create multipath links to the receiver [9].

Reference [21] introduced the use of a passive RIS in SR to improve both primary and secondary transmissions. The approach involved optimizing the active beamforming at the PTx and the passive reflection beamforming at the RIS to achieve a reduction in the PT's power consumption, subject to the QoS requirements of both PU and SU. The non-convex nature of the problem was tackled through alternating optimization (AO).

Another use of RIS is to work as a SU which can modulate and send its signal on the reflected signal of the PTx as in [17], [22] and [23]. In [17], a passive RIS is assisting MIMO SR communication system in a way that it works as a secondary transmitter to a secondary receiver and helps in reconfiguring the communication

channel intelligently. For optimizing an unmanned aerial vehicle (UAV) trajectory, the authors in [22] explored the use of RIS-assisted SR setup to enhance the overall performance of the system. Moreover, Hua. et.al, [23], propose a novel SR paradigm optimizing bit error rate (BER) for both CSR and PSR under rate constraint of PU's transmission.

However, passive RIS can enhance the performance of SR as well as the primary communication, it is a passive component that cannot amplify the signal. As a result, passive RIS can not eliminate the double-fading issue completely, causing limited enhancement in the performance.

In order to face this challenge, researchers have been investigating the use of active RIS with amplification capabilities which can amplify the incident signals as well as reconfigure the channel phases [9]. In [24], a downlink communication system consists of a PTx, a PU, active RIS and an eavesdropper has been investigated. They aimed to enhance the reliability by eliminating the multiplicative fading effect through using of active RIS while guaranteeing the PLS of the PU. The secrecy outage probability (SOP) was used as QoS metric. In [25], a single user with either an active or passive RIS assists the communication with the access point by creating another link due to the blockage of the direct link. This study considers both downlink and uplink communications. They optimized RIS placements in order to maximize the rate. In this study, a common amplification factor was considered to be optimized along with optimizing the phase shifts.

In [26], a comparative study is conducted to investigate the performance of both active and passive RIS under a fixed power budget. This study concluded the advantage of active RIS when the power budget is high enough and the number of

RIS elements is not too large.

Due to the vulnerability of wireless mediums to different security attacks, PLS can be a key player, especially for low-capacity users such as SR sensors. It is worth mentioning the PLS can be easily deployed in RIS-assisted communication systems such as in [27], [28], [29]. Moreover, passive RIS has been considered to assist the PLS in SR communication system as in [30]. In [3], the first to investigate the use of active RIS to enhance PLS in SR setup. They optimized both transmit beamforming at the PTx and the reflection beamforming at the active RIS constraints to QoS constraints. They aimed to protect the information transmitted to multi-PU in a multicast communication mode. However, they did not consider the security of the SU's information in their study. Moreover, they considered only the multicast scenario which is not usually the practical case, in which the PTx in most of the cases sends different messages to different users which is called multi-user beamforming communication mode as explained in previous subsections.

Building on and motivated by all the above studies, this thesis aims to cover the gaps in the previous research by focusing on a fully secure SR communications, where both scenarios (i.e., the multicast and multi-user beamforming communication modes) have been considered, aiming to reduce the total power consumption subject to QoS and security constraints.

1.3 Thesis Contributions

The main contributions of this thesis are summarized as follows

1. In Chapter 2, the multicast communication mode considered where a joint

beamforming optimization at both the PTx and the active RIS to minimize total power consumption subject to QoS constraints for the PUs and SU while maintaining security against eavesdroppers has been conducted. The system consists of multiple single antenna PUs, an active RIS to reflect and amplify the incident signal while sending its sensing information to a single antenna SU. The system also includes two types of eavesdroppers—one attempting to decode PUs’ signal, and another intercepting the SU’s signal.

2. Due to the lack of available CSI for the eavesdroppers’ channels, two CSI error models were employed: the worst-case (bounded) CSI error model and the statistical (outage probability) model.

3. The non-convex problem is addressed using an alternating optimization (AO) due to the fact such a problem cannot be solved for the global optimal solution, we evaluated the proposed algorithm by comparing it with Gradient search optimization for small-scale systems. Therefore, the original problem is decomposed into two subproblems: one for optimizing the transmit beamforming and the other for optimizing the reflection beamforming at the active RIS.

4. Numerical analysis was done to evaluate the performance of the proposed AO Algorithm 1, with results presented in Chapter 2.

5. In Chapter 3, the multi-user beamforming communication mode was considered in the same SR setup. This introduced new challenges due to interuser interference, making even the two subproblems in Chapter 2 non-convex too. To address this, a novel approach was adopted:

- The original problem is divided into three subproblems.
- Each SINR for the PUs and SU is divided into two components in the two

subproblems, each with its own threshold, iteratively updated as part of subproblem 3.

- A worst-case scenario was assumed, considering that each eavesdropper employs strong successive interference cancellation (SIC) techniques to eliminate interference from other users.
6. The proposed Algorithm (3) in Chapter 3 is validated through simulations.

CHAPTER 2

MULTICAST BEAMFORMING

In this chapter, the multicast communication mode is considered where the PTx sends the same confidential information to all PUs. In other words, only one transmit beamforming vector needs to be optimized. This chapter starts by defining the system model, power consumption under this mode, CSI uncertainty model. After that, the problem is formulated under the two CSI error models with the proposed solutions for each one. Finally, the results and conclusions are discussed.

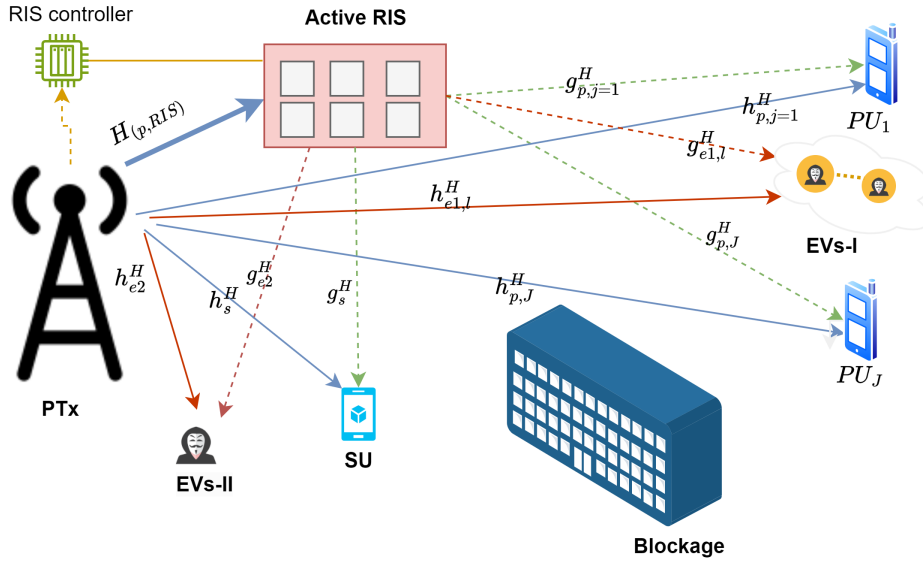


Figure 2.1: SR system model setup.

In Fig. 2.1, we illustrate the system model for secure communication in the SR

setup, assisted by an active RIS. The system comprises one primary transmitter (PTx) equipped with multiple antennas, one active RIS with reflective components, a single-antenna secondary user (SU), and multiple single-antenna primary users (PUs). There are two types of eavesdroppers (EVs-I and EVs-II), each equipped with a single antenna. EVs-I aims to intercept sensitive data being transmitted from the PTx to the PUs in the downlink channel, and it is assumed to be located close to the PUs. EVs-II, on the other hand, targets the sensing information backscattered by the active RIS to the SU and is assumed to be near the SU. The system operates by having the PTx broadcast signal containing sensitive information to all PUs via the active RIS to establish a reliable communication link. We assume that the link between EVs-I and SU is unavailable due to blockages, as EVs-I primarily targets the PUs. Similarly, the links between EVs-II and PUs are unavailable because their primary interest lies in SU's information. Refer back to Table 1.2 for channel descriptions of the system.

2.1 Signal Model

In this subsection, the signal model is introduced as well as the average SNR of each receiving node in the system. The received signal κ at the j^{th} PU during one secondary symbol can be written as

$$y_{p,j}(\kappa) = \mathbf{h}_{p,j}^H \mathbf{f} \mathbf{s}(\kappa) + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{f} \mathbf{s}(\kappa) + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{n}_{RIS}(\kappa) + n_j(\kappa), \quad \kappa \in \mathcal{K}, \quad j \in \mathcal{J} \quad (2.1)$$

where $\kappa \in \mathcal{K}$ and $\mathcal{K} = \{1, \dots, K\}$ is the set of all primary symbol, $\mathbf{f} \in \mathbb{C}^{M \times 1}$, $\mathbf{\Theta} \in \mathbb{C}^{N \times N}$, $\mathbf{n}_{RIS}(\kappa) \sim \mathcal{CN}(0, \sigma_{RIS}^2 \mathbf{I}_N)$, and $n_j(\kappa) \sim \mathcal{CN}(0, \sigma_j^2)$ are the transmit beamforming vector at the PT, the diagonal matrix of the reflection beamforming vector at the active RIS, the thermal noise for the active RIS due to the amplification, and additive-white-gaussian-noise (AWGN) at the j^{th} PU receiver, respectively.

As in [3], the binary phase shift keying (BPSK) technique is employed at the RIS to modulate the signal of the SU, where $v \in \{1, -1\}$. Consequently, the average SNR required at the j^{th} PU, considering the expectation over v , is expressed as follows:

$$\begin{aligned} \Psi_{p,j} &= E_v \left[\frac{|(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H(v\mathbf{\Theta})\mathbf{H}_{(P,RIS)})\mathbf{f}|^2}{(\sigma_{p,j}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta} v\|^2)} \right] \\ &= \frac{|(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})\mathbf{f}|^2}{2(\sigma_{p,j}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2)} + \frac{|(\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})\mathbf{f}|^2}{2(\sigma_{p,j}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2)}, \quad j \in \mathcal{J}. \end{aligned} \quad (2.2)$$

While SU's received signal can be denoted as $y_s(\kappa)$,

$$y_s(\kappa) = \mathbf{h}_s^H \mathbf{f}_s(\kappa) + \mathbf{g}_s^H(v\mathbf{\Theta})\mathbf{H}_{(P,RIS)}\mathbf{f}_s(\kappa) + \mathbf{g}_s^H(v\mathbf{\Theta})\mathbf{n}_{RIS}(\kappa) + n_s(\kappa), \quad \kappa \in \mathcal{K} \quad (2.3)$$

where $n_s(\kappa) \sim \mathcal{CN}(0, \sigma_s^2)$ is the AWGN at the SU. The maximum likelihood detection can be used to jointly decode both $\mathbf{s}(\kappa)$ and v [17]. Therefore, we can write the average SNR in order to decode $\mathbf{s}(\kappa)$ at the SU as follows:

$$\Psi_s^{s(\kappa)} = \frac{|(\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})\mathbf{f}|^2}{2(\sigma_s^2 + \sigma_{RIS}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2)} + \frac{|(\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})\mathbf{f}|^2}{2(\sigma_s^2 + \sigma_{RIS}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2)} \quad (2.4)$$

After getting the $\mathbf{s}(\boldsymbol{\kappa})$, SIC can be used to remove the direct link, i.e., the PT-SU link. Therefore, the remaining signal can be represented in the sense of the secondary symbol period. Let's denote it as $\tilde{y}_s$, where

$$\begin{aligned}\tilde{y}_s = [\tilde{y}_s(1), \dots, \tilde{y}_s(K)] &= \mathbf{g}_s^H(v\boldsymbol{\Theta})\mathbf{H}_{(P,RIS)}\mathbf{f}[s(1), \dots, s(K)]^T \\ &+ \mathbf{g}_s^H(v\boldsymbol{\Theta})[n_{RIS}(1), \dots, n_{RIS}(K)]^T \\ &+ [n_s(1), \dots, n_s(K)]^T.\end{aligned}\quad (2.5)$$

Utilizing the MRC technique [3], the approximate average SNR for decoding v at the SU is given by [31]

$$\Psi_s^v \approx \frac{K |(\mathbf{g}_s^H \boldsymbol{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}|^2}{(\sigma_s^2 + \sigma_{RIS}^2 \|\mathbf{g}_s^H \boldsymbol{\Theta}\|^2)}, \quad K \gg 1. \quad (2.6)$$

For the two types of eavesdroppers, the same principle can be applied as in equations (2.2), (2.4), and (2.6). For EVs-I, the received signal at the l^{th} EVs-I is formulated as

$$y_{e1,l}(\boldsymbol{\kappa}) = \mathbf{h}_{e1,l}^H \mathbf{f} \mathbf{s}(\boldsymbol{\kappa}) + \mathbf{g}_{e1,l}^H(v\boldsymbol{\Theta})\mathbf{H}_{(P,RIS)}\mathbf{f} \mathbf{s}(\boldsymbol{\kappa}) + \mathbf{g}_{e1,l}^H(v\boldsymbol{\Theta})\mathbf{n}_{RIS}(\boldsymbol{\kappa}) + n_{e1,l}(\boldsymbol{\kappa}), \quad k \in \mathcal{K}, l \in \mathcal{L} \quad (2.7)$$

Therefore, the average SNR at the l^{th} EVs for decoding $\mathbf{s}(\boldsymbol{\kappa})$ can be written as

$$\begin{aligned}
\Psi_{e1,l} &= E_v \left[\frac{|\left(\mathbf{h}_{e1,l}^H + \mathbf{g}_{e1,l}^H(v\mathbf{\Theta})\mathbf{H}_{(P,RIS)}\right)\mathbf{f}|^2}{\left(\sigma_{e1,l}^2 + \sigma_{RIS}^2\|\mathbf{g}_{e1,l}^H\mathbf{\Theta}v\|^2\right)} \right] \\
&= \frac{|\left(\mathbf{h}_{e1,l}^H + \mathbf{g}_{e1,l}^H\mathbf{\Theta}\mathbf{H}_{(P,RIS)}\right)\mathbf{f}|^2}{2\left(\sigma_{e1,l}^2 + \sigma_{RIS}^2\|\mathbf{g}_{e1,l}^H\mathbf{\Theta}\|^2\right)} + \frac{|\left(\mathbf{h}_{e1,l}^H - \mathbf{g}_{e1,l}^H\mathbf{\Theta}\mathbf{H}_{(P,RIS)}\right)\mathbf{f}|^2}{2\left(\sigma_{e1,l}^2 + \sigma_{RIS}^2\|\mathbf{g}_{e1,l}^H\mathbf{\Theta}\|^2\right)}, \\
&\quad l \in \mathcal{L}
\end{aligned} \tag{2.8}$$

On the other hand, EVs-II will follow exactly the same techniques applied by the SU. Through out of this work, we denoted the second type of eavesdroppers by the character $e2$ in order to distinguish between the two types. As a result, the received signals as well as the average SNR for decoding both the $\mathbf{s}(\boldsymbol{\kappa})$ and v at the EVs-II can be written as follows

$$\begin{aligned}
y_{e2}(\boldsymbol{\kappa}) &= \mathbf{h}_{e2}^H \mathbf{f} \mathbf{s}(\boldsymbol{\kappa}) + \mathbf{g}_{e2}^H(v\mathbf{\Theta})\mathbf{H}_{(P,RIS)} \mathbf{f} \mathbf{s}(\boldsymbol{\kappa}) + \mathbf{g}_{e2}^H(v\mathbf{\Theta})\mathbf{n}_{RIS}(\boldsymbol{\kappa}) \\
&\quad + n_{e2}(\boldsymbol{\kappa}), \quad \boldsymbol{\kappa} \in \mathcal{K},
\end{aligned} \tag{2.9}$$

And after using the SIC technique as well,

$$\begin{aligned}
\tilde{y}_{e2} &= [\tilde{y}_{e2}(1), \dots, \tilde{y}_{e2}(K)] = \mathbf{g}_{e2}^H(v\mathbf{\Theta})\mathbf{H}_{(P,RIS)} \mathbf{f} [s(1), \dots, s(K)]^T \\
&\quad + \mathbf{g}_{e2}^H(v\mathbf{\Theta})[n_{RIS}(1), \dots, n_{RIS}(K)]^T + [n_{e2}(1), \dots, n_{e2}(K)]^T,
\end{aligned} \tag{2.10}$$

While equation 2.11 will not be used, it is worth mentioning here. Average SNR at the EVs-II for decoding $\mathbf{s}(\boldsymbol{\kappa})$ is

$$\Psi_{e2}^{s(\kappa)} = \frac{|\left(\mathbf{h}_{e2}^H + \mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}\right) \mathbf{f}|^2}{2(\sigma_{e2}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2)} + \frac{|\left(\mathbf{h}_{e2}^H - \mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}\right) \mathbf{f}|^2}{2(\sigma_{e2}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2)} \quad (2.11)$$

Where for decoding v ,

$$\Psi_{e2}^v \approx \frac{K |\left(\mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}\right) \mathbf{f}|^2}{(\sigma_{e2}^2 + \sigma_{RIS}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2)}, \quad K \gg 1 \quad (2.12)$$

2.2 CSI Uncertainty Model

In SR system, both the PUs and SU are mutually working and cooperate with the PTx, and the channels (direct or through RIS channels) can be estimated as have been proposed by several researchers [32], [33], [34]. It is logical to assume perfect knowledge of the channels for the PUs and the SU at the PT. The estimation of the channels related to the eavesdroppers (Eves) can be logically explained as follows: In a scenario where the Eves are part of a multi-group primary communication system, they and the primary users (PUs) communicate with the PTx in alternating secondary symbol periods. Although the Eves are not authorized to access the information intended for the PUs, they attempt to intercept it during the periods when the PUs are being served. Meanwhile, during the periods when the Eves are being served, their channel state information (CSI) can be approximately obtained. As a result, the two types of eavesdroppers are not willing to cooperate with the PTx for channel estimation, for this reason, acquiring the correct CSI of their channels is challenging. To solve this problem, two CSI error models are used in this paper, the bounded CSI error model which can be considered as an upper

bound of the CSI errors, and the statistical CSI error model [3].

2.2.1 Bounded CSI Error Model

In this model, the worst case CSI error model for all the channels' estimated errors related to the EVs are assumed to be less or equal to a certain threshold (i.e., uncertainty radii), which is known to PTx. In general, for any channel, we can express this uncertainty as

$$\mathbf{h}_{e1,l} = \hat{\mathbf{h}}_{e1,l} + \Delta\mathbf{h}_{e1,l}, \quad \Delta\mathbf{h}_{e1,l} \in \mathbb{C}^{M \times 1}, \|\Delta\mathbf{h}_{e1,l}\|_2 \leq \beta_l, \quad \forall l \in \mathcal{L}, \quad (2.13)$$

The same thing will be applied to the rest of the channels (i.e., EVs-I $\mathbf{g}_{e1,l}$, EVs-II $\mathbf{h}_{e2}$ and $\mathbf{g}_{e2}$).

2.2.2 Statistical CSI Error Model

For this type of channel CSI uncertainty, the errors of the channels will follow a certain distribution. According to [29], [35], and [3], the CSI errors estimated at the PTx can be modeled as CSCG.

$$\mathbf{h}_{e1,l} = \hat{\mathbf{h}}_{e1,l} + \Delta\mathbf{h}_{e1,l}, \quad \Delta\mathbf{h}_l \in \mathbb{C}^{M \times 1}, \Delta\mathbf{h}_{e1,l} \sim \mathcal{CN}(0, \Sigma_{h,l}), \quad \Sigma_{h,l} \succeq 0, \quad (2.14)$$

where the variance of $\Delta\mathbf{h}_l$ can be modeled as $\varepsilon_{h,l}^2 = \xi_{h,l}^2 \|\hat{\mathbf{h}}_l\|_2^2$ in which $\xi_{h,l} \in [0, 1)$ are the CSI uncertainty of the channel $\mathbf{h}_{e1,l}$. The same will be applied to all other EV channels. On the other hand, of the bounded CSI error model, the estimated

CSI errors can be modeled as

$$\beta_{h,l} = \sqrt{\frac{\varepsilon_{h,l}^2}{2} F_D^{-1}(1 - \rho_l)} \quad (2.15)$$

In which $F_D^{-1}(\cdot)$ is the inverse cumulative distribution function of the Chi-square distribution with D denoting the degree of freedom in which in this work it is equal to $2M$ for direct channels and $2N$ for the RIS related channels. ρ_l is the outage probability of the l^{th} - EVs. It is worth noting that the previously mentioned CSI error model facilitates an equitable comparison of robust beamforming designs under both the bounded and statistical CSI error models [36].

2.3 Power Consumption

2.3.1 Active RIS

Due to the existence of active RIS, the total power consumption can be calculated as follows

$$P_{total} = P_{PTx} + P_{active,RIS} - P_{incident} \quad (2.16)$$

In which $P_{PTx} = \|\mathbf{f}\|^2$ represents the PT's transmitted power. For the active RIS, power consumption can be calculated for RIS with N reflecting elements as in [37],

$$P_{active,RIS} = N(P_{SW} + P_{DC}) + \|\mathbf{\Theta}\mathbf{H}_{(P,RIS)}\mathbf{f}\|^2 + \sigma_{RIS}^2\|\mathbf{\Theta}\|^2 \quad (2.17)$$

where P_{DC} denotes the direct current biasing consumed power at each RIS element, P_{SW} is the switch and control power of each RIS element, and $\|\mathbf{\Theta}\mathbf{H}_{(P,RIS)}\mathbf{f}\|^2 + \sigma_{RIS}^2\|\mathbf{\Theta}\|^2$ represents the output power of the active RIS [9]. Moreover, the incident

power, $P_{\text{incident}} = \|\mathbf{H}_{(P,\text{RIS})}\mathbf{f}\|$, must be subtracted from the total power consumption to ensure an accurate calculation of the overall system power.

2.3.2 Passive RIS

The passive RIS has been considered as a benchmark scheme in this thesis. The total power consumption in this case can be calculated as in [26]

$$P_{\text{total}} = P_{PTx} + P_{\text{passive},\text{RIS}} \quad (2.18)$$

In which $P_{PTx} = \|\mathbf{f}\|^2$ represents the PT's transmitted power. For the circuit power of the passive RIS, it can be expressed as

$$P_{\text{passive},\text{RIS}} = N(P_{\text{SW}}) \quad (2.19)$$

Because the RIS is passive, the noise power is typically neglected.

2.4 Problem Formulation and Proposed Solution

In this section, the problem formulation and the proposed solution under two different CSI error models, bounded and statistical CSI error models for the channels of all the types of EVs are introduced.

2.4.1 Bounded CSI Error Model

The problem is formulated to minimize the system's total power consumption while ensuring the confidentiality of both the PT-PU and RIS-SU communications as well as the QoS. The optimization problem is defined as

$$\min_{\mathbf{f}, \Theta} \quad \|\mathbf{f}\|^2 + N(P_{\text{SW}} + P_{\text{DC}}) + \|\Theta \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}\|^2 + \sigma_{\text{RIS}}^2 \|\Theta\|^2 - \|\mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}\|^2$$

s.t.

$$\text{C1: } \Psi_{p,j} \geq \Psi_{s(\kappa)}, \quad j \in \mathcal{J},$$

$$\text{C2: } \Psi_S^{(\kappa)} \geq \Psi_{s(\kappa)},$$

$$\text{C3: } \Psi_S^v \geq \Psi_v,$$

$$\text{C4: } \Psi_{e1,l} \leq \Psi_{\text{EVS-I}},$$

$$\|\Delta \mathbf{h}_l\|_2 \leq \beta_{h,l}, \quad \|\Delta \mathbf{g}_l\|_2 \leq \beta_{g,l}, \quad l \in \mathcal{L},$$

$$\text{C5: } \Psi_{S,e2}^v \leq \Psi_{\text{EVS-II}},$$

$$\|\Delta \mathbf{h}_{e2}\|_2 \leq \beta_{h,e2}, \quad \|\Delta \mathbf{g}_{e2}\|_2 \leq \beta_{g,e2},$$

$$\text{C6: } 0 \leq a_n \leq \rho, \quad 0 \leq \phi_n \leq 2\pi, \quad n \in \mathbf{N}, \quad (\text{P1})$$

where $\Psi_{s(\kappa)}$, Ψ_v , $\Psi_{\text{EVS-I}}$, and $\Psi_{\text{EVS-II}}$ are the decoding SNR of the primary transmission, the decoding SNR of the secondary transmission, the maximum SNR threshold at EVs-I to decode the $s(\kappa)$ and the maximum SNR threshold at EVs-II to decode v , respectively. C1 sets the minimum SNR at the PU to decode $s(\kappa)$, C2 and C3 guarantee the minimum SNR level at the SU first to decode $s(\kappa)$ and then uses SIC technique to decode v . Constraint C4 ensures a secure transmission toward the PU by setting the maximum achievable SNR gained at EVs-I to be lower than the threshold needed to decode the $s(\kappa)$ at EVs-I under the bounded CSI error. Constraint C5 is used to secure the information v sent by the active RIS against EVs-II. Constraint C6 is related to the reflection parameters of the active RIS.

The non-convexity of P1 is due to the joint optimization of both $\mathbf{f}$ and Θ variables, making it challenging to find a global optimal solution for P1. Therefore, an (AO) algorithm consists of two steps optimization is proposed by dividing the problem into two subproblems and solving iteratively. The transmit beamforming vector $\mathbf{f}$ is optimized first, then the result from $\mathbf{f}$ is used as an input to the second part which is optimizing the reflection beamforming Θ .

Before presenting the solution, we first introduce **Lemma 1**, which will be utilized to reformulate constraints C4 and C5 into linear matrix inequalities (LMIs). This reformulation is necessary to address the uncertainty in the channels associated with the two types of Eves.

Lemma 1: (S-Procedure [35]) Let $\mathbf{A}_c \in \mathbb{H}^{n \times n}$, $\mathbf{u}_c \in \mathbb{C}^n$, $h_c \in \mathbb{R}$, where $c = \{1, 2\}$. Suppose there exists a point x satisfying the following quadratic function of x as

$$f(x) = x^H \mathbf{A}_1 x + 2\Re(\mathbf{u}_1^H x) + a_1$$

Then, these inequalities

$$\begin{aligned} x^H \mathbf{A}_1 x + 2\Re(\mathbf{u}_1^H x) + a_1 &\leq 0 \\ x^H \mathbf{A}_2 x + 2\Re(\mathbf{u}_2^H x) + a_2 &\leq 0 \end{aligned} \tag{2.20}$$

hold for $\forall x$ if and only if there exists a constant $\nu \geq 0$ such that

$$\nu \begin{bmatrix} \mathbf{A}_1 & \mathbf{u}_1 \\ \mathbf{u}_1^H & a_1 \end{bmatrix} \succeq \begin{bmatrix} \mathbf{A}_2 & \mathbf{u}_2 \\ \mathbf{u}_2^H & a_2 \end{bmatrix}. \tag{2.21}$$

Transmit Beamforming Optimization

In this subsection, the transmit beamforming $\mathbf{f}$ is optimized while fixing the reflection beamforming under the bounded CSI error model. Firstly, we introduce an auxiliary variable $\mathbf{F}$ where $\mathbf{F} = \mathbf{f}\mathbf{f}^H$, $\text{Rank}(\mathbf{F})$ and $\mathbf{F} \succeq \mathbf{0}$ in order to convert the subproblem into a tractable form to be solved using CVX solver. As a result, C1, C2, and C3 can be reformulated as

$$\begin{aligned} \text{C8: } \quad & \text{Tr}(\mathbf{H}_{p,j}\mathbf{F}) + \text{Tr}(\mathbf{H}_{(\text{P,RIS,PU},j)}\mathbf{F}) \geq \Psi_{s(\kappa)} \left(\sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \boldsymbol{\Theta}\|^2 \right), \\ & j \in \mathcal{J}, \end{aligned}$$

$$\text{C9: } \quad \text{Tr}(\mathbf{H}_s\mathbf{F}) + \text{Tr}(\mathbf{H}_{(\text{P,RIS,SU})}\mathbf{F}) \geq \Psi_{s(\kappa)} \left(\sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \boldsymbol{\Theta}\|^2 \right),$$

$$\text{C10: } \quad K \text{Tr}(\mathbf{H}_{(\text{P,RIS,SU})}\mathbf{F}) \geq \Psi_v \left(\sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \boldsymbol{\Theta}\|^2 \right),$$

where the $\mathbf{H}_{(\text{P,RIS,PU},j)}$ and $\mathbf{H}_{(\text{P,RIS,SU})}$ can be reformulated as

$$\mathbf{H}_{(\text{P,RIS,PU},j)} = \left(\mathbf{g}_{p,j}^H \boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \right)^H \left(\mathbf{g}_{p,j}^H \boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \right),$$

$$\mathbf{H}_{(\text{P,RIS,SU})} = \left(\mathbf{g}_s^H \boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \right)^H \left(\mathbf{g}_s^H \boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \right),$$

$$\mathbf{H}_{p,j} = \mathbf{h}_{p,j} \mathbf{h}_{p,j}^H, \quad \mathbf{H}_s = \mathbf{h}_s \mathbf{h}_s^H.$$

For C4 and C5, the S-Procedure in **Lemma 1** will be used to equivalently consider the uncertainties in the estimation error of the channels, after reformulating

them as follows

$$\begin{aligned} \text{C4: } \Delta \mathbf{x}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} + \Delta \mathbf{x}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} + \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} \Delta \mathbf{x}_{e1,l} + \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} &\leq \Psi_{EVS-I} \sigma_{e1,l}^2, \\ \|\Delta \mathbf{x}_{e1,l}\|^2 &\leq \beta_{h,l}^2 + \beta_{g,l}^2, \quad l \in \mathcal{L}, \end{aligned} \quad (2.22)$$

where

$$\begin{aligned} \tilde{\mathbf{F}} &= \begin{bmatrix} \mathbf{\Theta} \mathbf{H}_{(P,RIS)} \mathbf{F} \mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H - \Psi_{EVS-I} \sigma_{RIS}^2 \mathbf{\Theta} \mathbf{\Theta}^H & \mathbf{0} \\ \mathbf{0} & \mathbf{F} \end{bmatrix} \\ \mathbf{x}_{e1,l} &= \begin{pmatrix} \mathbf{g}_{e1,l} \\ \mathbf{h}_{e1,l} \end{pmatrix}, \quad \hat{\mathbf{x}}_{e1,l} = \begin{pmatrix} \hat{\mathbf{g}}_{e1,l} \\ \hat{\mathbf{h}}_{e1,l} \end{pmatrix}, \quad \Delta \mathbf{x}_{e1,l} = \begin{pmatrix} \Delta \mathbf{g}_{e1,l} \\ \Delta \mathbf{h}_{e1,l} \end{pmatrix}. \end{aligned}$$

Therefore, the equivalent LMI can be formulated for $l \in \mathcal{L}$ as follows,

$$\nu_{e1,l} \begin{bmatrix} \mathbf{I}_{N+M} & \mathbf{0} \\ \mathbf{0} & -\beta_l^2 \end{bmatrix} \preceq \begin{bmatrix} \tilde{\mathbf{F}} & \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} \\ \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} & \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} - \Psi_{EVS-I} \sigma_{e1,l}^2 \end{bmatrix}, \quad (2.23)$$

where $\nu_{e1,l} \geq 0$ is a slack variable for the l -th EVs-I and needs to be optimized in accordance with the

$$\beta_l^2 = \beta_{h,l}^2 + \beta_{g,l}^2.$$

We can notice that 2.23 is derived from (2.21) by replacing the variables in Lemma 1 as follows,

$$x = \Delta x_{e1,l}, \quad A_1 = I_{M+N}, \quad u_1 = \mathbf{0}, \quad u_2 = \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l}, \quad a_1 = -\beta_l^2,$$

$$A_2 = \tilde{\mathbf{F}}, \quad a_2 = \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} - \Psi_{EVS-I} \sigma_{e1,l}^2.$$

Then C4 constraint can be rewritten as follows by moving the left side to the

right side with a negative sign and now the equivalent constraint will be denoted as C11 as

C11:

$$\text{LMI}_{e1,l}^F = \begin{bmatrix} \nu_{e1,l} \mathbf{I}_{N+M} - \tilde{\mathbf{F}} & -\tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} \\ -\hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} & -\nu_{e1,l} \beta_l^2 - \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}} \hat{\mathbf{x}}_{e1,l} + \Psi_{EVS-1} \sigma_{e1,l}^2 \end{bmatrix} \succeq \mathbf{0}$$

where $\text{LMI}_{e1,l}^F \in \mathbb{C}^{(N+M+1) \times (N+M+1)}$,

Similarly, for constraint C5, it can be approximated as,

$$\Delta \mathbf{x}_{e2}^H \tilde{\mathbf{F}}_{e2} \Delta \mathbf{x}_{e2} + \Delta \mathbf{x}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} + \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \Delta \mathbf{x}_{e2} + \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} \leq \Psi_{EVS_{II}} \sigma_{e2}^2,$$

$$\|\Delta \mathbf{x}_{e2}\|^2 \leq \beta_{g,e2}^2,$$

where $\mathbf{x}_{e2} = \mathbf{g}_{e2}$, $\hat{\mathbf{x}}_{e2} = \hat{\mathbf{g}}_{e2}$, $\Delta \mathbf{x}_{e2} = \Delta \mathbf{g}_{e2}$, and $\beta_{e2} = \beta_{g,e2}^2$, this is because the SNR for decoding the v at the EVs-II only depends on the uncertainty of the channel related to the RIS-EVs-II. The LMI for this type of Eavesdroppers would be as follows,

$$\nu_{e2} \begin{bmatrix} \mathbf{I}_N & \mathbf{0} \\ \mathbf{0} & -\beta_{e2}^2 \end{bmatrix} \succeq \begin{bmatrix} \tilde{\mathbf{F}}_{e2} & \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} \\ \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} & \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} - \frac{1}{K} \Psi_{EVS_{II}} \sigma_{e2}^2 \end{bmatrix}, \quad (2.24)$$

where,

$$\tilde{\mathbf{F}}_{e2} = \mathbf{\Theta} \mathbf{H}_{(P,RIS)} \mathbf{F} \mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H - \frac{1}{K} \Psi_{EVS_{II}} \sigma_{RIS}^2 \mathbf{\Theta} \mathbf{\Theta}^H,$$

Now the LMI for approximating C5 can be expressed as,

C12:

$$LMI_{e2}^F = \begin{bmatrix} \nu_{e2} \mathbf{I}_N - \tilde{\mathbf{F}}_{e2} & -\tilde{\mathbf{F}}_{e2} \hat{\mathbf{g}}_{e2} \\ -\hat{\mathbf{g}}_{e2}^H \tilde{\mathbf{F}}_{e2} & -\nu_{e2} \beta_{e2}^2 - \hat{\mathbf{g}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{g}}_{e2} + \frac{1}{K} \Psi_{EVs_{II}} \sigma_{e2}^2 \end{bmatrix} \succeq \mathbf{0}$$

Where $LMI_{e2}^F \in \mathbb{C}^{(N+1) \times (N+1)}$

Then, the new subproblem for optimizing $\mathbf{F}$ can be written as

$$\begin{aligned} \min_{\mathbf{F}, \nu_{e1}, \nu_{e2}} \quad & \text{Tr}(\mathbf{F}) + \text{Tr}((\mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}) - \text{Tr}(\mathbf{H}_{(P,RIS)}^H \mathbf{H}_{(P,RIS)} \mathbf{F}) \\ \text{s.t.} \quad & C8, C9, C10, C11, C12, \\ & C13 : \text{Rank}(\mathbf{F}) = 1 \\ & C14 : \mathbf{F} \succeq \mathbf{0} \end{aligned} \tag{P2}$$

Subproblem 2 is still nonconvex due to constraint C14. After relaxing C14 by using SDR methods, P2 can be reformulated as in (P3).

$$\begin{aligned} \min_{\mathbf{F}, \nu_{e1}, \nu_{e2}} \quad & \text{Tr}(\mathbf{F}) + \text{Tr}((\mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}) - \text{Tr}(\mathbf{H}_{(P,RIS)}^H \mathbf{H}_{(P,RIS)} \mathbf{F}) \\ \text{s.t.} \quad & C8, C9, C10, C11, C12, C14 \end{aligned} \tag{P3}$$

P3 can be solved efficiently since it is converted to a relaxed semidefinite programming (SDP), which can be solved using methods such as the interior-point method. Simulation results show that the suboptimal $\mathbf{F}^*$ is always of rank one. To ensure the results will always be ranked one, the Gaussian randomization technique is used only if the result is not ranked one. The eigenvalue decomposition is

used to get the suboptimal beamforming vector, i.e., $\mathbf{f}^{*(t)}$ at the t^{th} iteration [31].

Reflection Beamforming Optimization

After getting the $\mathbf{F}^{(t)}$, we optimized Θ while fixing $\mathbf{F}$. Assume $\mathbf{p} = [p_1, \dots, p_N]^T$ to be the vector of the diagonal elements of Θ , by introducing a similar variable $\mathbf{P} = \mathbf{p}\mathbf{p}^H$, $\mathbf{P} \succeq 0$, $\text{Rank}(\mathbf{P}) = 1$, $P(n, n) \leq \rho^2$, $n \in \mathcal{N}$. Then, C1, C2, and C3 can be rewritten as follows

$$\text{C15: } \text{Tr}(\mathbf{H}_{p,j}\mathbf{F}) + \text{Tr}(\mathbf{H}_{(\mathbf{P},\text{RIS},\text{PU},j)}\mathbf{P}) - (\sigma_{\text{RIS}}^2 \mathbf{g}_{p,j}^H \mathbf{P} \mathbf{g}_{p,j}) \Psi_{s(\kappa)} \geq \sigma_j^2 \Psi_{s(\kappa)}, \quad j \in \mathcal{J}$$

$$\text{C16: } \text{Tr}(\mathbf{H}_s\mathbf{F}) + \text{Tr}(\mathbf{H}_{(\mathbf{P},\text{RIS},\text{SU})}\mathbf{P}) - (\sigma_{\text{RIS}}^2 \mathbf{g}_s^H \mathbf{P} \mathbf{g}_s) \Psi_{s(\kappa)} \geq \sigma_s^2 \Psi_{s(\kappa)}$$

$$\text{C17: } K \text{Tr}(\mathbf{H}_{(\mathbf{P},\text{RIS},\text{SU})}\mathbf{P}) - (\sigma_{\text{RIS}}^2 \mathbf{g}_s^H \mathbf{P} \mathbf{g}_s) \Psi_v \geq \sigma_v^2 \Psi_v,$$

where

$$\mathbf{H}_{(P,\text{RIS},\text{PU},j)} = \text{diag}(\mathbf{H}_{(P,\text{RIS})}\mathbf{f}) \mathbf{g}_{p,j} \mathbf{g}_{p,j}^H \text{diag}(\mathbf{H}_{(P,\text{RIS})}\mathbf{f})^H,$$

$$\mathbf{H}_{(\mathbf{P},\text{RIS},\text{SU})} = \text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f}) \mathbf{g}_s \mathbf{g}_s^H \text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f})^H,$$

Also, the S-Procedure (i.e., **Lemma 1**) is used to deal with constraints C4, and C5.

For C4, $\bar{\mathbf{P}}$ is defined as

$$\bar{\mathbf{P}} = \begin{bmatrix} \text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f})\mathbf{P}\text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f})^H - \sigma_{\text{RIS}}^2 \Psi_{\text{EVS}-1} \mathbf{P} & \mathbf{0} \\ \mathbf{0} & \mathbf{F} \end{bmatrix};$$

$$\text{C18: LMI}_{\mathbf{P}}^l = \begin{bmatrix} \bar{\nu}_{e1,l} \mathbf{I}_{N+M} - \bar{\mathbf{P}} & -\bar{\mathbf{P}} \hat{\mathbf{x}}_{e1,l} \\ -\hat{\mathbf{x}}_{e1,l}^H \bar{\mathbf{P}} & -\bar{\nu}_{e1,l} \beta_l^2 - \hat{\mathbf{x}}_{e1,l}^H \bar{\mathbf{P}} \hat{\mathbf{x}}_{e1,l} + \Psi_{\text{EVS-1}} \sigma_{e1,l}^2 \end{bmatrix} \succeq \mathbf{0}, \quad l \in \mathcal{L}$$

Similarly, for constraint C5,

$$\bar{\mathbf{P}}_{e2} = \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}) \mathbf{P} \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f})^H - \sigma_{\text{RIS}}^2 \frac{1}{K} \Psi_{\text{EVS-II}} \mathbf{P}$$

$$\text{C19: LMI}_{\mathbf{P}}^{e2} = \begin{bmatrix} \bar{\nu}_{e2} \mathbf{I}_N - \bar{\mathbf{P}}_{e2} & -\bar{\mathbf{P}}_{e2} \hat{\mathbf{x}}_{e2} \\ -\hat{\mathbf{x}}_{e2}^H \bar{\mathbf{P}}_{e2} & -\bar{\nu}_{e2} \beta_{e2}^2 - \hat{\mathbf{x}}_{e2}^H \bar{\mathbf{P}}_{e2} \hat{\mathbf{x}}_{e2} + \frac{1}{K} \Psi_{\text{EVS-II}} \sigma_{e2}^2 \end{bmatrix} \succeq \mathbf{0}$$

Therefore, the subproblem to optimize the $\mathbf{P}$ can be reformulated as

$$\min_{\mathbf{P}, \bar{\nu}_{e1}, \bar{\nu}_{e2}} \text{Tr} \left(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f})^H \mathbf{P} \right) + \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P})$$

subject to

$$\text{C15, C16, C17, C18, C19}$$

$$\text{C20: Rank}(\mathbf{P}) = 1$$

$$\text{C21: } \mathbf{P} \succeq \mathbf{0}$$

$$\text{C22: } P(n, n) \leq \rho^2, \quad n \in \mathcal{N} \quad (\text{P4})$$

Subproblem 4 is still non-convex due to the rank-one constraint (i.e., C20). After dropping C20, the problem can be solved using CVX solver (i.e., SDP) followed by

Gaussian randomization. The objective function in P4 is very small as compared to the AO tolerance for convergence. For better convergence of the algorithm, we can introduce the SNR residuals for C16, C17, and C18 constraints, where SNR residuals represent the slack variables that quantify the gap between the actual SNR achieved in the system and the required SNR defined by constraints. By introducing these residuals, the constraints become less rigid, allowing the optimization algorithm to handle infeasibility more gracefully. As a result, the problem can be reformulated as a maximization subproblem as in P5.

$$\max_{\mathbf{P}, \bar{\nu}_{e1}, \bar{\nu}_{e2}, \gamma} -\text{Tr} \left(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f})^H \mathbf{P} \right) - \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P}) + \sum_{j=1}^{J+2} \gamma_j$$

s.t.

$$\bar{C15}: \text{Tr}(\mathbf{H}_{p,j} \mathbf{F}) + \text{Tr} \left(\mathbf{H}_{(\mathbf{P}, \text{RIS}, \text{PU}, j)} \mathbf{P} \right) - \left(\sigma_{\text{RIS}}^2 \mathbf{g}_{p,j}^H \mathbf{P} \mathbf{g}_{p,j} \right) \Psi_{s(\kappa)} \geq$$

$$\sigma_j^2 \left(\Psi_{s(\kappa)} + \gamma_j \right), \quad j \in \mathcal{J},$$

$$\bar{C16}: \text{Tr}(\mathbf{H}_s \mathbf{F}) + \text{Tr} \left(\mathbf{H}_{(\mathbf{P}, \text{RIS}, \text{SU})} \mathbf{P} \right) - \left(\sigma_{\text{RIS}}^2 \mathbf{g}_s^H \mathbf{P} \mathbf{g}_s \right) \Psi_{s(\kappa)} \geq$$

$$\sigma_s^2 \left(\Psi_{s(\kappa)} + \gamma_{J+1} \right),$$

$$\bar{C17}: K \text{Tr}(\mathbf{H}_{(\mathbf{P}, \text{RIS}, \text{SU})} \mathbf{P}) - \left(\sigma_{\text{RIS}}^2 \mathbf{g}_s^H \mathbf{P} \mathbf{g}_s \right) \Psi_v \geq \sigma_s^2 \left(\Psi_v + \gamma_{J+2} \right),$$

$$\text{C18, C19, C21, and C22} \tag{P5}$$

The suboptimal $\mathbf{P}^*$ will be decomposed using eigenvalue decomposition followed by Gaussian randomization to get the suboptimal $\mathbf{p}^*$ vector. These solution steps are described in detail in Algorithm 1 as well as in the flowchart in Figure. 2.2.

Algorithm 1 AO Algorithm 1 for Solving (P1)

```
1: Initialization: Iteration index  $t = 0$ , convergence tolerance  $\Xi$ , reflection
   beamforming vector  $\mathbf{p}^{(t)}$ .
2: repeat
3:   Solve P3 for  $\mathbf{F}^{(t)}$ .
4:   if  $\text{rank}(\mathbf{F}^{(t)}) = 1$  then
5:     Compute eigenvalue decomposition of  $\mathbf{F}^{(t)}$  as  $\mathbf{F}^{(t)} = \mathbf{U}_1 \mathbf{\Sigma}_1 \mathbf{U}_1^H$ .
6:     Extract solution from the leading eigenvector of  $\mathbf{F}^{(t)}$  as  $\mathbf{f}^{(t)}$ .
7:     Go to step 18
8:   else
9:     for  $i = 1, \dots, \text{maxIterations}$  do
10:      Generate a Gaussian random vector  $\mathbf{g}_i$  with zero mean and unit
      variance.
11:      Construct candidate solution  $\mathbf{f}_i = \mathbf{U}_1 \mathbf{\Sigma}_1^{1/2} \mathbf{g}_i$ .
12:      if (P3) is feasible with  $\mathbf{f}_i$  then
13:        Compute objective value with  $\mathbf{f}_i$ .
14:      end if
15:    end for
16:    return  $\mathbf{f}^{(t)} = \mathbf{f}_{i^*}$ , where  $i^* = \arg \min \text{objective}(i)$ .
17:  end if
18:  With updated  $\mathbf{f}^{(t)}$ , optimize reflection beamforming to get  $\mathbf{p}^{(t+1)}$ .
19:  Solve P5 for  $\mathbf{p}^{(t+1)}$ .
20:  if  $\text{rank}(\mathbf{P}^{(t+1)}) = 1$  then
21:    Compute eigenvalue decomposition of  $\mathbf{P}^{(t+1)}$  as  $\mathbf{P}^{(t+1)} = \mathbf{U}_1 \mathbf{\Sigma}_1 \mathbf{U}_1^H$ .
22:    Extract solution from the leading eigenvector of  $\mathbf{P}^{(t+1)}$ .
23:    Go to step 34
24:  else
25:    for  $i = 1, \dots, \text{maxIterations}$  do
26:      Generate a Gaussian random vector  $\mathbf{g}_i$  with zero mean and unit
      variance.
27:      Construct candidate solution  $\mathbf{p}_i = \mathbf{U}_1 \mathbf{\Sigma}_1^{1/2} \mathbf{g}_i$ .
28:      if (P5) is feasible with  $\mathbf{p}_i$  then
29:        Compute objective value with  $\mathbf{p}_i$ .
30:      end if
31:    end for
32:    return  $\mathbf{p}^{(t+1)} = \mathbf{p}_{i^*}$ , where  $i^* = \arg \min \text{objective}(i)$ .
33:  end if
34:  Update  $t = t + 1$ .
35: until the difference between  $\text{Objective}(t + 1)$  and  $\text{Objective}(t)$  is smaller than
    $\Xi$ .
```

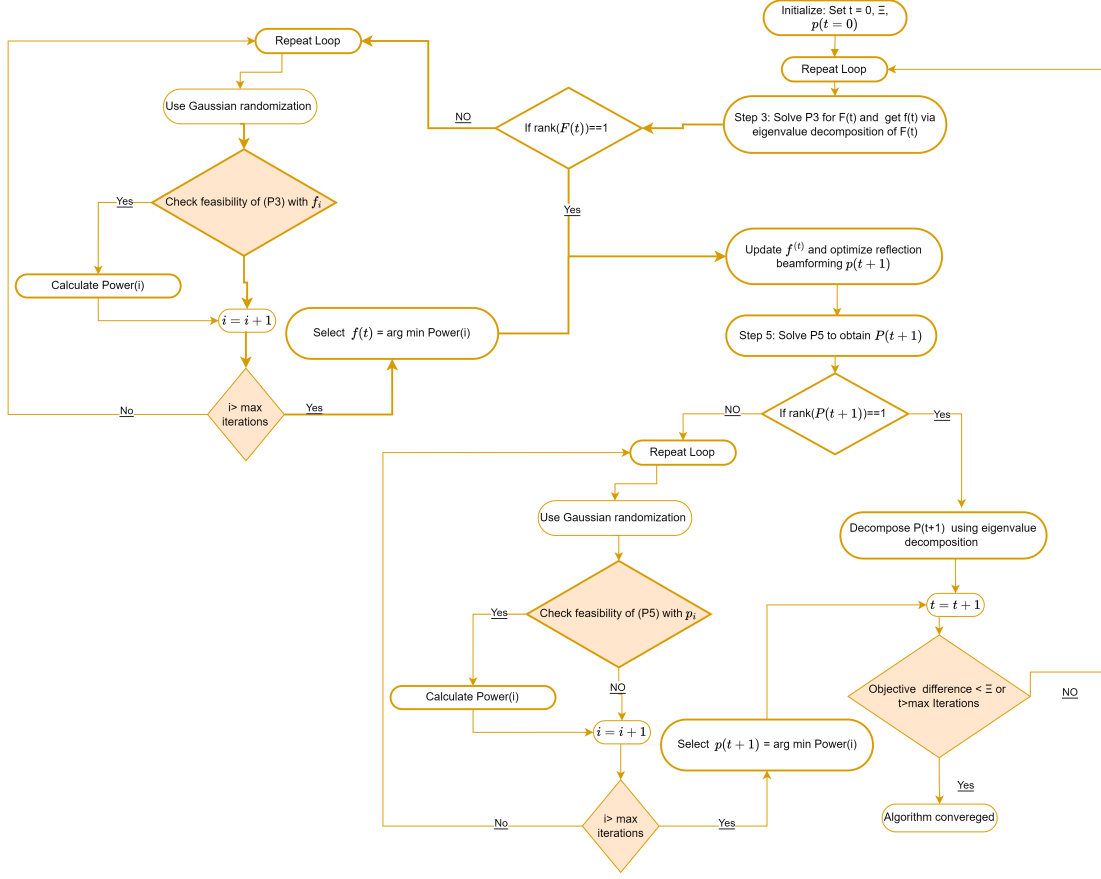


Figure 2.2: The flowchart of Algorithm 1

2.4.2 Statistical CSI Error Model

The formulation in P1 remains the same, except that the approach to handling channel uncertainty for the two types of eavesdroppers will now be modified. Since the estimation error usually follows a Gaussian distribution, which has no bound, we introduce the statistical CSI error model in this subsection and solve the same problem in terms of outage probability $p_{e1,l}$ constant at the l^{th} EVs-I and p_{e2} is the outage probability at EVs-II.

Therefore,

$$\text{C23: } \Pr \{ \Psi_l \leq \Psi_{\text{EVs-I}} \} \geq 1 - p_{e1,l} \quad (2.25)$$

$$\Delta \mathbf{h}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,l}), \quad l \in \mathcal{L}$$

Similarly, C5 in P1 will also be written as,

$$\text{C24: } \Pr \{ \Psi_{e2}^v \leq \Psi_{\text{EVs-II}} \} \geq 1 - p_{e2}$$

$$\Delta \mathbf{g}_{e2} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,e2}) \quad (2.26)$$

As a result, P1 will be reformulated as

$$\begin{aligned} \min_{\mathbf{f}, \Theta} \quad & \|\mathbf{f}\|^2 + N(P_{SW} + P_{DC}) + \|\Theta \mathbf{H}_{(\text{P,RIS})} \mathbf{f}\|^2 + \sigma_{RIS}^2 \|\Theta\|^2 \\ \text{s.t.} \quad & \text{C1, C2, C3, C7, C23, C24} \quad (\text{P6}) \end{aligned}$$

P6 is also a non-convex problem and a similar AO in Algorithm 1 will be used, where the transmit beamforming vector will be first optimized at loop t , then the resultant $f^{(t)}$ will be used to optimize the reflection beamforming of the RIS. For tackling the CSI uncertainty error of the EVs channel, we propose the use of Bernstein-Type Inequality to reformulate C23, and C24, SDR technique, and Gaussian randomization to solve the problem iteratively. Before proceeding to the solution, let's introduce the Bernstein-Type Inequality in *Lemma 2*.

Lemma 2: (Lemma 5 in [35] and Lemma 2 in [3]) Considering $f(y) = y^H \mathbf{W} y + 2\Re\{\mathbf{b}^H y\} + b$, where $\mathbf{W} \in \mathbb{H}^{S \times S}$, $\mathbf{b} \in \mathbb{C}^{S \times 1}$, $b \in \mathbb{R}$, and $y \in \mathbb{C}^{S \times 1} \sim \mathcal{CN}(0, I_S)$. If there exists a variable satisfying $p \in [0, 1]$, the following approximation can be

obtained

$$\Pr\{f(y) \geq 0\} \geq 1 - p \quad (2.27)$$

$$\Rightarrow \text{Tr}\{\mathbf{W}\} - \sqrt{2 \ln\left(\frac{1}{p}\right)} \sqrt{\|\mathbf{W}\|_F^2 + 2\|\mathbf{b}\|^2} + \ln(p)\lambda_{\max}^+(-\mathbf{W}) + b \geq 0 \quad (2.28)$$

$$\Rightarrow \begin{cases} \text{Tr}\{\mathbf{W}\} - \sqrt{2 \ln\left(\frac{1}{p}\right)}e + \ln(p)c + h \geq 0 \\ \sqrt{\|\mathbf{W}\|_F^2 + 2\|\mathbf{b}\|^2} \leq z \\ c\mathbf{I}_S + \mathbf{W} \geq 0, \quad c \geq 0, \end{cases} \quad (2.29)$$

Where $\lambda_{\max}^+(-\mathbf{W}) = \max(\lambda_{\max}(-\mathbf{W}), 0)$. c and z are slack variables. In the upcoming subsections, we introduce the solution of both $\mathbf{F}$ and $\mathbf{\Theta}$ optimization.

Transmit Beamforming Optimization

As in algorithm 1, we first perform optimization of the $\mathbf{F}$ given $\mathbf{\Theta}$. All the constraints unrelated to the EVs will remain the same as in P3. Therefore, C23 can be reformulated as

$$\text{C23: } \Pr\left\{\sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \left(\mathbf{h}_{e1,l}^H \mathbf{F} \mathbf{h}_{e1,l} + \mathbf{g}_{e1,l}^H \mathbf{B}_f^{e1,l} \mathbf{g}_{e1,l}\right) \geq 0\right\} \geq 1 - p_{e1,l}, \quad (2.30)$$

$$\Delta \mathbf{h}_{e1,l} \sim \mathcal{CN}(0, \Sigma_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(0, \Sigma_{g,l}), \quad l \in \mathcal{L}$$

Where

$$\mathbf{B}_f^{e1,l} = \mathbf{\Theta} H_{(P,\text{RIS})} \mathbf{F} H_{(P,\text{RIS})}^H \mathbf{\Theta}^H - \Psi_{\text{EVs-I}} \sigma_{\text{RIS}}^2 \mathbf{\Theta} \mathbf{\Theta}^H$$

According to [3], this equation has no closed form which can be approximated as in Lemma 2 to make it computationally flexible and easy to handle by first assuming $\Sigma_{g,l} = \xi_{g,l}^2 I_N$ and $\Sigma_{h,l} = \xi_{h,l}^2 I_M$ [29], [35]. Therefore, $\Delta \mathbf{h}_{e1,l} = \xi_{h,l} i_{h,l}$, $\Delta \mathbf{g}_{e1,l} = \xi_{g,l} i_{g,l}$, where $i_{h,l} \sim \mathcal{CN}(0, I_M)$ and $i_{g,l} \sim \mathcal{CN}(0, I_N)$. As a result, equation (2.22) can be reformulated as

$$\Pr \{ i_l^H \mathbf{W}_{e1,l} i_l + 2 \text{Re}\{\mathbf{b}_{e1,l}^H i_l\} + b_{e1,l} \geq 0 \} \geq 1 - p_{e1,l}, \quad l \in \mathcal{L} \quad (2.31)$$

Where

$$\mathbf{W}_{e1,l} = \begin{bmatrix} -\xi_{g,l}^2 \mathbf{B}_f^{e1,l} & 0 \\ 0 & -\xi_{h,l}^2 \mathbf{F} \end{bmatrix}, \quad \mathbf{b}_{e1,l}^H = \begin{bmatrix} -\xi_{g,l} \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_f^{e1,l} & -\xi_{h,l} \hat{\mathbf{h}}_{e1,l}^H \mathbf{F} \end{bmatrix},$$

$$b_{e1,l} = \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \hat{\mathbf{h}}_{e1,l}^H \mathbf{F} \hat{\mathbf{h}}_{e1,l} - \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_f^{e1,l} \hat{\mathbf{g}}_{e1,l}, \text{ and } \mathbf{i}_l = \begin{pmatrix} i_{g,l} \\ i_{h,l} \end{pmatrix}$$

By using Lemma 2, we can approximate this constraint as follows while introducing slack variables $\mathbf{c} = [c_1, \dots, c_{e1,l}]$ and $\mathbf{z} = [z_1, \dots, z_{e1,l}]$,

$$\text{Tr}\{\mathbf{W}_{e1,l}\} - \sqrt{2 \ln \left(\frac{1}{p_{e1,l}} \right)} z_{e1,l} + \ln(p_{e1,l}) c_{e1,l} + b_{e1,l} \geq 0, \quad l \in \mathcal{L}, \quad (2.32)$$

$$\sqrt{\|\mathbf{W}_{e1,l}\|_F^2 + 2\|\mathbf{b}_{e1,l}\|^2} \leq z_{e1,l}, \quad l \in \mathcal{L}, \quad (2.33)$$

$$c_{e1,l}\mathbf{I}_{M+N} + \mathbf{W}_{e1,l} \succeq \mathbf{0}, \quad l \in \mathcal{L}. \quad (2.34)$$

To simplify (2.33), we can rewrite it as

$$\left\| \begin{array}{c} \xi_{g,l}^2 \text{vec}(\mathbf{B}_f^{e1,l}) \\ \xi_{h,l}^2 \text{vec}(\mathbf{F}) \\ \sqrt{2} \xi_{g,l} \mathbf{B}_f^{e1,l} \hat{\mathbf{g}}_{e1,l} \\ \sqrt{2} \xi_{h,l} \mathbf{F} \hat{\mathbf{h}}_{e1,l} \end{array} \right\| \leq z_{e1,l}, \quad l \in \mathcal{L} \quad (2.35)$$

In the same way, constraint C24 can be approximated by first considering

$$\Pr \{ \mathbf{i}_{e2}^H \mathbf{W}_{e2} \mathbf{i}_{e2} + 2\Re \{ \mathbf{b}_{e2}^H \mathbf{i}_{e2} \} + b_{e2} \geq 0 \} \geq 1 - p_{e2} \quad (2.36)$$

where $\mathbf{W}_{e2} = -\xi_{g,e2}^2 \mathbf{B}_f^{e2}$, $\mathbf{b}_{e2}^H = [-\xi_{g,e2} \hat{\mathbf{g}}_{e2}^H \mathbf{B}_f^{e2}]$, $b_{e2} = \sigma_{e2}^2 \frac{1}{K} \Psi_{(EVs-II)} - \hat{\mathbf{g}}_{e2}^H \mathbf{B}_f^{e2} \hat{\mathbf{g}}_{e2}$, $\mathbf{B}_f^{e2} = \mathbf{\Theta} \mathbf{H}_{(P,RIS)} \mathbf{F} \mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H - \frac{1}{K} \Psi_{(EVs-II)} \sigma_{RIS}^2 \mathbf{\Theta} \mathbf{\Theta}^H$ and $\mathbf{i}_{e2} = \mathbf{i}_{g,e2}$. Therefore, C24 can be approximated as

$$\text{Tr}\{\mathbf{W}_{e2}\} - \sqrt{2 \ln \left(\frac{1}{p_{e2}} \right)} z_{e2} + \ln(p_{e2}) c_{e2} + b_{e2} \geq 0 \quad (2.37)$$

$$\left\| \begin{array}{c} \xi_{g,e2}^2 \text{vec}(\mathbf{B}_f^{e2}) \\ \sqrt{2} \xi_{g,e2} \mathbf{B}_f^{e2} \hat{\mathbf{g}}_{e2} \end{array} \right\| \leq z_{e2} \quad (2.38)$$

$$c_{e2} \mathbf{I}_N + \mathbf{W}_{e2} \succeq \mathbf{0}, \quad (2.39)$$

Therefore, the subproblem will be similar to P2, where only the constraint of the

eavesdropper, the uncertainty will be tackled under the statistical error model.

$$\begin{aligned} \min_{\mathbf{F}, \mathbf{c}_{e1}, \mathbf{z}_{e1}, \mathbf{c}_{e2}, \mathbf{z}_{e2}} \quad & \text{Tr}(\mathbf{F}) + \text{Tr} \left((\mathbf{H}_{(P, \text{RIS})}^H \mathbf{\Theta}^H \mathbf{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{F} \right) - \text{Tr} \left(\mathbf{H}_{(P, \text{RIS})}^H \mathbf{H}_{(P, \text{RIS})} \mathbf{F} \right) \\ \text{s.t.} \quad & C8, C9, C10, C14, (2.32), (2.34), (2.35), (2.37), (2.38), \text{ and } (2.39) \quad (\text{P6}) \end{aligned}$$

Reflection Beamforming Optimization

In this subproblem, a similar problem to **P5** will be solved, only constraints related to eavesdroppers will be approximated as in subsection A. With the given $\mathbf{F}^{(t)}$ by solving **P6**, we will focus on optimizing $\mathbf{P}^{(t+1)}$ under this CSI error model. **C23** can be reformulated as

$$\begin{aligned} \Pr \left\{ \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \left(\mathbf{h}_{e1,l}^H \mathbf{F} \mathbf{h}_{e1,l} + \mathbf{g}_{e1,l}^H \mathbf{B}_P^{e1,l} \mathbf{g}_{e1,l} \right) \geq 0 \right\} &\geq 1 - p_{e1,l} \quad , \\ \Delta \mathbf{h}_{e1,l} &\sim \mathcal{CN}(0, \mathbf{\Sigma}_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(0, \mathbf{\Sigma}_{g,l}), \quad l \in \mathcal{L}, \end{aligned} \quad (2.40)$$

where $\mathbf{B}_P^{e1,l} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}) \mathbf{P} \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f})^H - \sigma_{\text{RIS}}^2 \Psi_{\text{EVs-I}} \mathbf{P}$. Similarly, by using the same analysis in Lemma 2, this constraint can be approximated as

$$\text{Tr}\{\mathbf{W}_{e1,l}\} - \sqrt{2 \ln \left(\frac{1}{p_{e1,l}} \right)} \bar{z}_{e1,l} + \ln(p_{e1,l}) \bar{c}_l + \bar{b}_{e1,l} \geq 0, \quad l \in \mathcal{L}, \quad (2.41)$$

$$\left\| \begin{array}{c} \xi_{g,l}^2 \text{vec} \left(\mathbf{B}_P^{e1,l} \right) \\ \xi_{h,l}^2 \text{vec} (\mathbf{F}) \\ \sqrt{2\xi_g} \mathbf{B}_P^{e1,l} \hat{\mathbf{g}}_{e1,l} \\ \sqrt{2\xi_h} \mathbf{F} \hat{\mathbf{h}}_{e1,l} \end{array} \right\| \leq \bar{z}_{e1,l}, \quad l \in \mathcal{L}, \quad (2.42)$$

$$\bar{c}_{e1,l} \mathbf{I}_{M+N} + \mathbf{W}_{e1,l} \succeq 0, \quad l \in \mathcal{L} \quad (2.43)$$

$$\text{where } \bar{\mathbf{W}}_{e1,l} = \begin{bmatrix} -\xi_{g,l}^2 \mathbf{B}_P^{e1,l} & \mathbf{0} \\ \mathbf{0} & -\xi_{h,l}^2 \mathbf{F} \end{bmatrix}, \quad \mathbf{b}_{e1,l}^H = \begin{bmatrix} -\xi_{g,l} \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_P^{e1,l} & -\xi_{h,l} \hat{\mathbf{h}}_{e1,l}^H \mathbf{F} \end{bmatrix},$$

$$b_{e1,l} = \sigma_{e1,l}^2 \Psi_{\text{EVS-I}} - \hat{\mathbf{h}}_{e1,l}^H \mathbf{F} \hat{\mathbf{h}}_{e1,l} - \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_P^{e1,l} \hat{\mathbf{g}}_{e1,l}, \quad \text{and } \mathbf{i}_l = \begin{pmatrix} \mathbf{i}_{g,l} \\ \mathbf{i}_{h,l} \end{pmatrix}.$$

Similarly, constraint C24 can be reformulated as,

$$\Pr \{ \mathbf{i}_{e2}^H \bar{\mathbf{W}}_{e2} \mathbf{i}_{e2} + 2\Re \{ \mathbf{h}_{o,2}^H \mathbf{i}_{e2} \} + h^{e2} \geq 0 \} \geq 1 - p_{e2},$$

$$\Delta \mathbf{g}_{e2} \sim \mathcal{CN}(0, \Sigma_{g,o}) \quad (2.44)$$

$$\text{where } \bar{\mathbf{W}}_{e2} = -\xi_{g,e2}^2 \mathbf{B}_P^{e2}, \mathbf{b}_{e2}^H = [-\xi_{g,e2} \hat{\mathbf{g}}_{e2}^H \mathbf{B}_P^{e2}],$$

$$b_{e2} = \sigma_{e2}^2 \frac{1}{K} \Psi_{(EVS-II)} - \hat{\mathbf{g}}_{e2}^H \mathbf{B}_P^{e2} \hat{\mathbf{g}}_{e2}, \mathbf{i}_{e2} = \mathbf{i}_{g,e2}.$$

and $\mathbf{B}_P^{e2} = \text{diag}(\mathbf{H}_{(P,RIS)} \mathbf{f}) \mathbf{P} \text{diag}(\mathbf{H}_{(P,RIS)} \mathbf{f})^H - \sigma_{\text{RIS}}^2 \frac{1}{K} \Psi_{(EVS-II)} \mathbf{P}$. This gives the final form of constraint C24 as follows,

$$\text{Tr}(\bar{\mathbf{W}}_{e2}) - \sqrt{2 \ln \left(\frac{1}{p_{e2}} \right)} \bar{z}_{e2} + \ln(p_{e2}) \bar{c}_{e2} + b_{e2} \geq 0 \quad (2.45)$$

$$\left\| \begin{bmatrix} \xi_{g,e2}^2 \text{vec}(\mathbf{B}_P^{e2}) \\ \sqrt{2} \xi_{g,e2} \mathbf{B}_P^{e2} \hat{\mathbf{g}}_{e2} \end{bmatrix} \right\| \leq \bar{z}_{e2} \quad (2.46)$$

$$\bar{c}_{e2}\mathbf{I}_N + \overline{\mathbf{W}}_{e2} \succeq \mathbf{0} \quad (2.47)$$

Therefore, the new subproblem in this subsection will be similar to P5 with the following modifications,

$$\begin{aligned} \max_{\mathbf{P}, \bar{\mathbf{z}}_{e1}, \bar{c}_{e1}, \bar{\mathbf{z}}_{e2}, \bar{c}_{e2}, \gamma} \quad & -\text{Tr} \left(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f})^H \mathbf{P} \right) - \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P}) + \sum_{j=1}^{J+2} \gamma_j \\ \text{s.t.}, \end{aligned}$$

$$\overline{C15}, \overline{C16}, \overline{C17}, C21, C22, (2.41), (2.42), (2.43), (2.45), (2.46), \text{ and } (2.47)(\mathbf{P7})$$

2.4.3 Gradient Search with Randomization Method

In this subsection, we discuss the gradient search with the randomization method, which was employed to evaluate the performance of the proposed algorithm in a small-scale system with $M = 2$ transmit antennas and $N = 2$ reflecting elements. This method serves as a benchmark to compare the suboptimal solution generated by our proposed algorithm.

The problem is formulated as:

$$\begin{aligned} \min_{\mathbf{f}, \Theta} \quad & \|\mathbf{f}\|^2 + N(P_{\text{SW}} + P_{\text{DC}}) + \|\Theta \mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}\|^2 + \sigma_{\text{RIS}}^2 \|\Theta\|^2 - \|\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}\|^2 \\ \text{s.t.} \quad & \\ \text{C1:} \quad & \Psi_{p,j} \geq \Psi_{s(\kappa)}, \quad j \in \mathcal{J}, \\ \text{C2:} \quad & \Psi_S^{(\kappa)} \geq \Psi_{s(\kappa)}, \\ \text{C3:} \quad & \Psi_S^v \geq \Psi_v, \\ \text{C6:} \quad & 0 \leq a_n \leq \rho, \quad 0 \leq \phi_n \leq 2\pi, \quad n \in \mathbf{N}, \quad (\text{P1}) \end{aligned}$$

where $\mathbf{f}$ is the beamforming vector, $\mathbf{\Theta}$ is the diagonal RIS phase shift matrix, P_{SW} is the power consumption per RIS element, P_{DC} is the direct current power, $\mathbf{H}_{(\text{P}, \text{RIS})}$ represents the channel between the transmitter and the RIS, and σ_{RIS}^2 is the noise variance at the RIS.

The gradient of the objective function is derived as follows:

$$\nabla_{\mathbf{f}}\mathcal{L} = 2\mathbf{f} + 2\mathbf{H}_{(\text{P}, \text{RIS})}^H \mathbf{\Theta}^H \mathbf{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f} - 2\mathbf{H}_{(\text{P}, \text{RIS})}^H \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}, \quad (2.48)$$

$$\nabla_{\mathbf{\Theta}}\mathcal{L} = 2\mathbf{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f} \mathbf{f}^H \mathbf{H}_{(\text{P}, \text{RIS})}^H + 2\sigma_{\text{RIS}}^2 \mathbf{\Theta}. \quad (2.49)$$

To solve the optimization problem, the method involves the following steps and follows Algorithm ??

1. Random initialization of $\mathbf{f}$ and $\mathbf{\Theta}$ for around 100,000 iterations.
2. Gradient descent optimization to minimize the objective function. The gradients $\nabla_{\mathbf{f}}\mathcal{L}$ and $\nabla_{\mathbf{\Theta}}\mathcal{L}$ are computed and used to update $\mathbf{f}$ and $\mathbf{\Theta}$ iteratively.
3. For each randomization, the algorithm checks only four constraints C_1 , C_2 , C_3 , and C_6 to simplify the process. These constraints are used for comparison purposes.
4. The solution with the smallest objective value that satisfies the constraints is selected as the optimal solution.

This approach ensures that the proposed algorithm produces a competitive suboptimal solution, demonstrating its effectiveness in meeting the constraints and achieving good performance. Using gradient search with extensive randomization provides a robust benchmark for comparison. To ensure a fair comparison, we

Algorithm 2 Gradient Search Optimization with Randomizations

- 1: **Input:** System parameters $H, N, P_{\text{SW}}, P_{\text{DC}}, \sigma_{\text{RIS}}, \dots$, number of randomizations num_randomizations, step size step_size, tolerance tol, maximum iterations max_iter.
- 2: **Output:** Optimal beamforming vector f_{opt} , optimal RIS matrix Θ_{opt} , objective value f_{val} .
- 3: **Initialization:**
- 4: Set best_f = $\emptyset$, best_Theta = $\emptyset$, best_obj_val = ∞ .
- 5: **for** rand_iter = 1 to num_randomizations **do**
- 6: **Generate random initial values:**

$$f_0 \sim \mathcal{CN}(0, I_M), \quad \Theta_0 = \text{diag}(\rho_n \cdot e^{j\theta_n}),$$

where ρ_n and θ_n are initial amplitudes and phases of n^{th} ARIS.

- 7: Set $f = f_0, \Theta = \Theta_0, \text{iter} = 0$.
 - 8: **while** iter < max_iter **do**
 - 9: Compute gradients:
$$\nabla_f = \text{GradientFunction}_f(f, \Theta), \quad \nabla_{\Theta} = \text{GradientFunction}_{\Theta}(f, \Theta).$$
 - 10: Update variables:
$$f \leftarrow f - \text{step_size} \cdot \nabla_f, \quad \Theta \leftarrow \Theta - \text{step_size} \cdot \nabla_{\Theta}.$$
 - 11: Evaluate objective function:
$$f_{\text{val}} = \text{ObjectiveFunction}(f, \Theta).$$
 - 12: **if** $\|\nabla_f\| < \text{tol}$ **and** $\|\nabla_{\Theta}\| < \text{tol}$ **then**
 - 13: **Break.**
 - 14: **end if**
 - 15: Increment iter $\leftarrow \text{iter} + 1$.
 - 16: **end while**
 - 17: **if** f and Θ satisfy constraints C_1, C_2, C_3, C_6 **and** $f_{\text{val}} < \text{best_obj_val}$ **then**
 - 18: Update best_f $\leftarrow f, \text{best_Theta} \leftarrow \Theta, \text{best_obj_val} \leftarrow f_{\text{val}}$.
 - 19: **end if**
 - 20: **end for**
 - 21: **Return:** $f_{\text{opt}} = \text{best_f}, \Theta_{\text{opt}} = \text{diag}(\text{best_Theta}), f_{\text{val}} = \text{best_obj_val}$.
-

evaluated the performance of our algorithm against Algorithm 2 by considering only the constraints C_1 , C_2 , C_3 , and C_6 across different values of Ψ_v .

2.5 Results and Discussion

In this section, we performed a numerical assessment of the proposed algorithm under various parameter settings for both CSI error models, focusing on the total system power consumption. Unless mentioned otherwise, the simulation parameters are provided in Table 2.1.

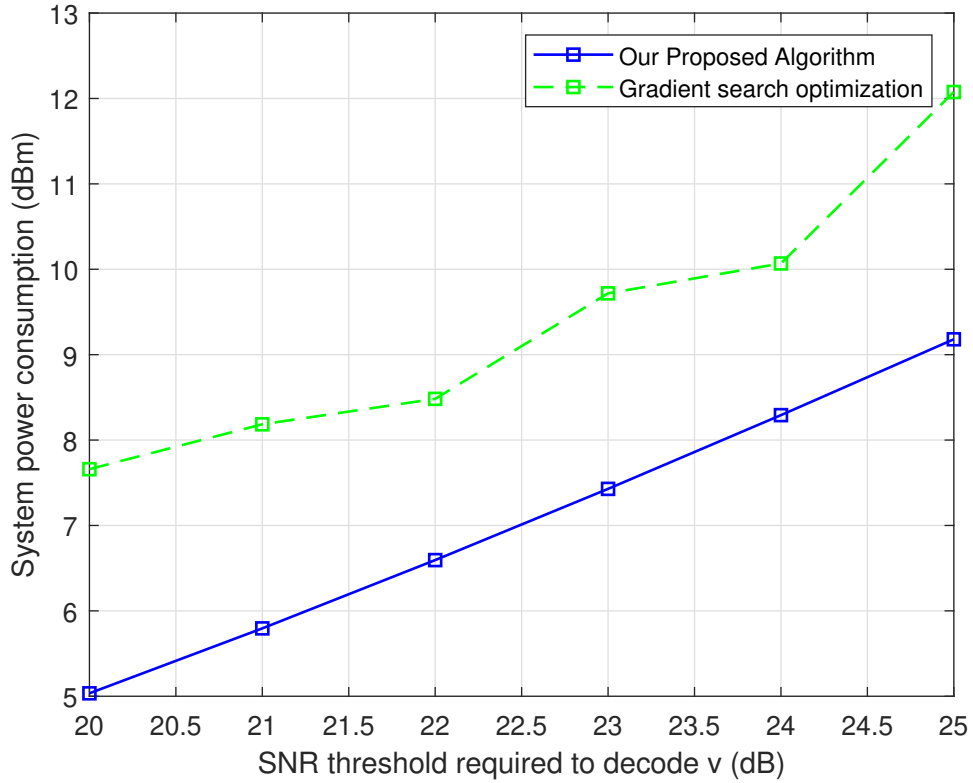


Figure 2.3: Comparison with the gradient search in Algorithm 2 with our proposed Algorithm.

Figure 3.2 illustrates a comparison between the proposed algorithm and the Gradient Search optimization method after executing 100,000 randomization tri-

Table 2.1: Simulation parameters 1

Parameter	Value
PTx location (x, y)	$(0, 0)$ m
Number of PUs	$J = 2$
Number of EVs-I	$\mathcal{L} = 2$
RIS location (x, y)	$(18, 5)$ m
SU location (x, y)	$(20, 0)$ m
PU locations, randomly placed around (x, y)	$(80, 4)$ m
EVs type I locations, randomly placed around (x, y)	$(80, 2)$ m
EVs type II locations, randomly placed around (x, y)	$(80, 2)$ m
Carrier frequency f_c	800 MHz
The path-loss exponents for channels related to RIS $\delta_{\text{transmitter, receiver}}$	$\delta_{\text{PU, RIS}} = 2.4,$ $\delta_{\text{RIS, EVs}} = 4,$ $\delta_{\text{RIS, SU}} = 3,$ $\delta_{\text{SU, PT}} = 2.4,$ $\delta_{\text{PT, RIS}} = 2.4$
For those unrelated to RIS δ	$\delta = 4$
The Rician factor Γ	5
PTx antennas no. M	$M = 6$
RIS reflection elements no. N	$N = 16$
All additive noise power σ^2	−90 dBm
The maximum amplification of the active RIS ρ^2	10
Direct current biasing power at each RIS element P_{DC}	−5 dBm
Switch and control power of each RIS element P_{SW}	−10 dBm
SNR thresholds	$\Psi_v = 40$ dB, $\Psi_{S(\kappa)} = 24$ dB, $\Psi_{EVs_I} = 15$ dB, $\Psi_{EVs_{II}} = 15$ dB
The amount of uncertainties for Eavesdropper channels	$\xi_{g_1} = \xi_{h_1} =$ $\xi_{g_2} = \xi_{h_0} = 0.02$
The outage probability $p_{e1,l}$ and p_{e2}	$p_{e1,l}=0.05$ and $p_{e2}=0.05$

als. The figure depicts the total power consumption as a function of the SNR required to decode v . While Algorithm 2 provides an effective solution for small-scale systems, the results clearly demonstrate that the proposed algorithm consistently outperforms the Gradient Search optimization method. This superior performance is attributed to the limitations of search-based methods like Gradient Search when handling constrained optimization problems. Specifically, projecting the solution onto the feasible set of constraints can significantly degrade the performance of

Gradient Search. Even with 100,000 randomization trials, the Gradient Search method fails to guarantee an optimal solution, underscoring the robustness of the proposed algorithm in comparison.

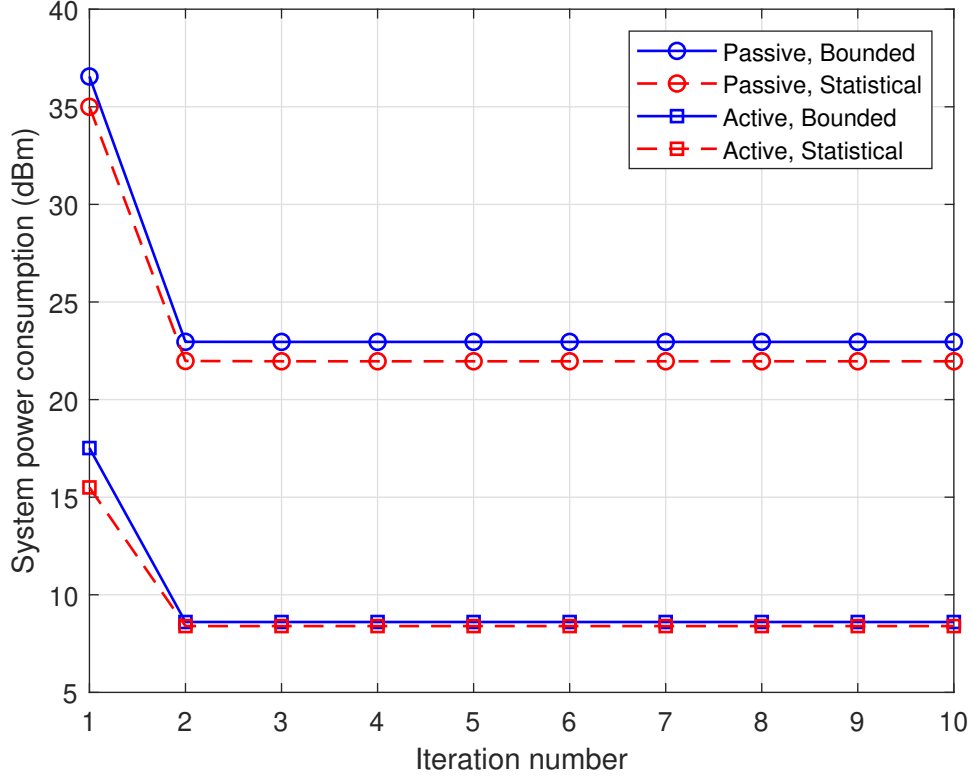


Figure 2.4: Convergence performance of Algorithm 1.

The convergence behavior of the algorithm is depicted in Figure 2.4. This figure provides a comparison of the convergence performance of the proposed algorithm at $\Psi_v = 40$ dB. The proposed method achieves significant power savings while ensuring secure communication within a limited number of iterations. We analyzed the convergence performance for both passive and active RIS scenarios, and the active RIS configuration shows a marked enhancement in overall system power efficiency. Furthermore, for both passive and active RIS, the statistical CSI error model leads to reduced power consumption compared to the bounded CSI error

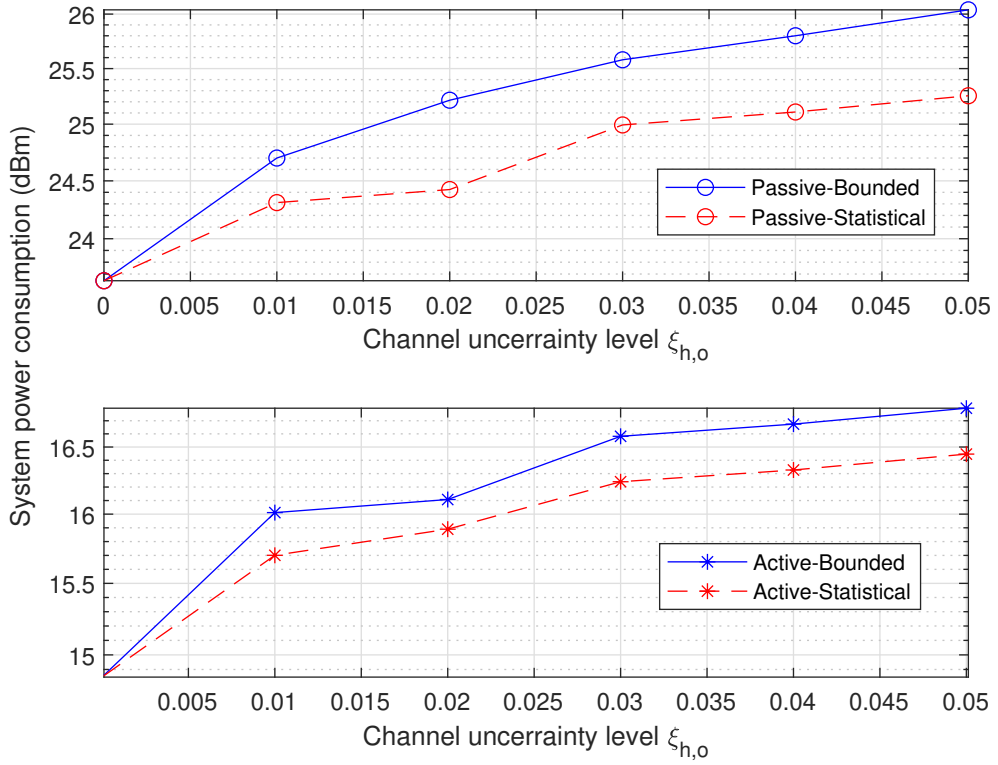


Figure 2.5: Total power consumption vs uncertainty level of the direct channel to EVs-II, ξ_{h_o} .

model.

The effect of increasing the uncertainty level of the second type (EVs-II) on the power consumption, with $\Psi_v = 65$ dB, $\Psi_{s(\kappa)} = 24$ dB is shown in Figure 2.5.

Figure 2.6 shows the total power consumption in both the presence and absence of the second type of eavesdroppers (i.e., EVs-II), considering two different numbers of active RIS elements. The results demonstrate that securing the information of the SU is possible with only a slight increase in power consumption. From the figure, it is evident that for $N = 20$, power consumption is higher than for $N = 15$ in the low SNR range, but as the SNR for decoding v increases (approximately 55 dB), the power consumption for $N = 20$ begins to fall below that of $N = 15$. Furthermore, in the low SNR range of the SU, the difference in power consumption

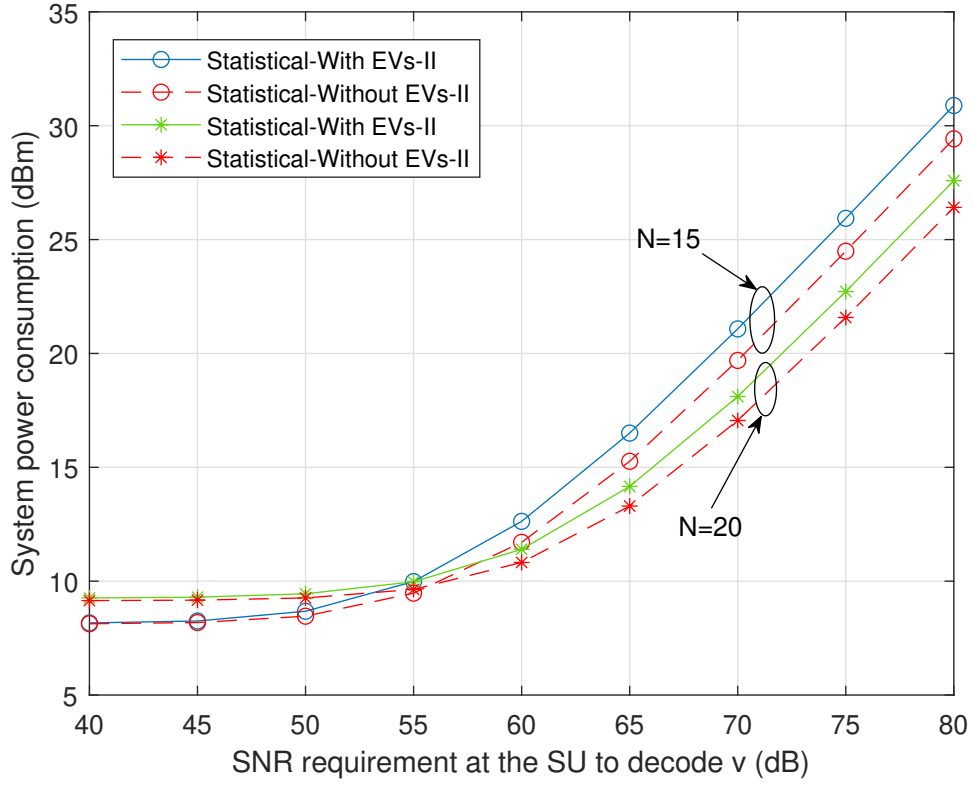


Figure 2.6: With SU's EVs and without power consumption vs SNR requirement to decode v , Ψ_v , with two different numbers active RIS elements (N).

between the cases with and without EVs-II is almost negligible.

Figure 2.7 plots the effect of increasing the number of RIS elements on the total power consumption with varying the amplification factor of the active RIS. The value of $\Psi_v = 65$, other parameters as in Table 2.1. As shown in this figure, as the number of active RIS elements increases, the performance gets better until reaching the point where increasing this number is not efficient due to the trade-off between the amplification gain and the power consumption of the active RIS with the number of reflection elements N . It is noticeable that as the amplification factor ρ^2 increases, RIS reaches its optimal number of reflection elements faster, i.e., $N^* = 30$ for $\rho^2 = 15$. After this point, the power consumption starts increasing again, while for $\rho^2 = 15$ this number N^* is higher. Moreover, passive RIS needs

many elements to reach the same performance as active RIS. As shown in the fig. 2.7, passive RIS reached the optimal point around $N=45$, where increasing the number of elements is no longer beneficial.

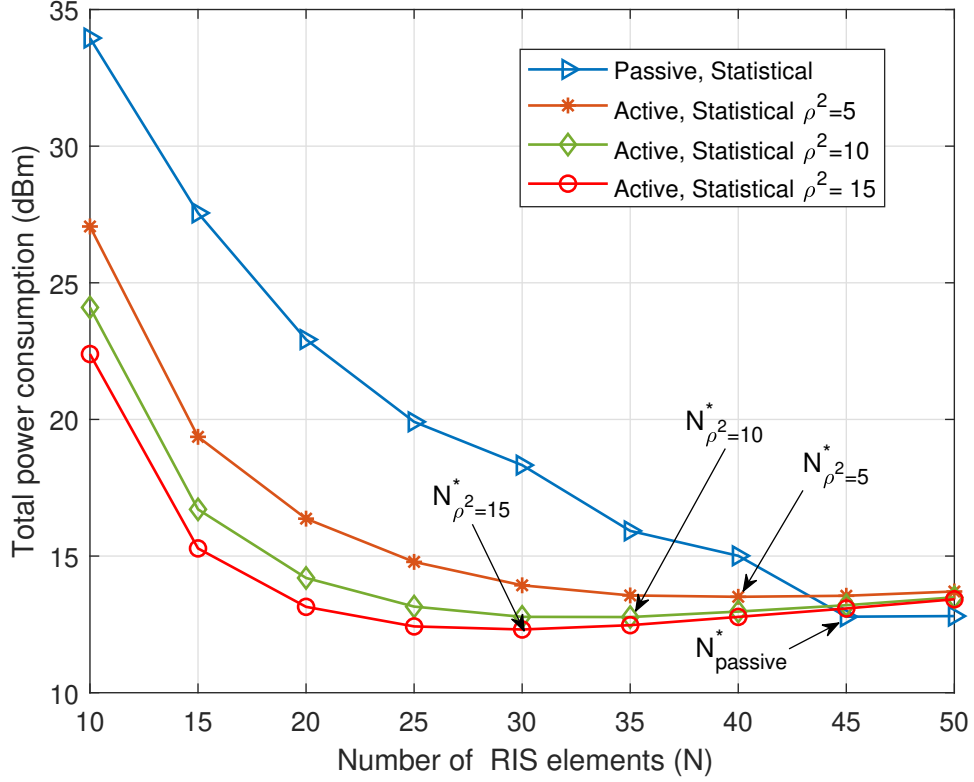


Figure 2.7: Power consumption vs RIS elements number (N) for different active RIS amplification factors ρ^2 .

Figure 2.8 shows the effect of increasing the SNR requirement for decoding $s(\kappa)$ for different M numbers under the statistical CSI error model. As shown in this figure, increasing the SNR (dB) will increase the power consumption to satisfy the constraints of all users. This figure is plotted at $\Psi_v=65$ dB. It is noticeable that for $M = 15$ higher power is consumed. As this number becomes higher, power consumption will be less but the difference between $M = 20$ and $M = 25$ is not significant due to the additional power consumption of the active RIS.

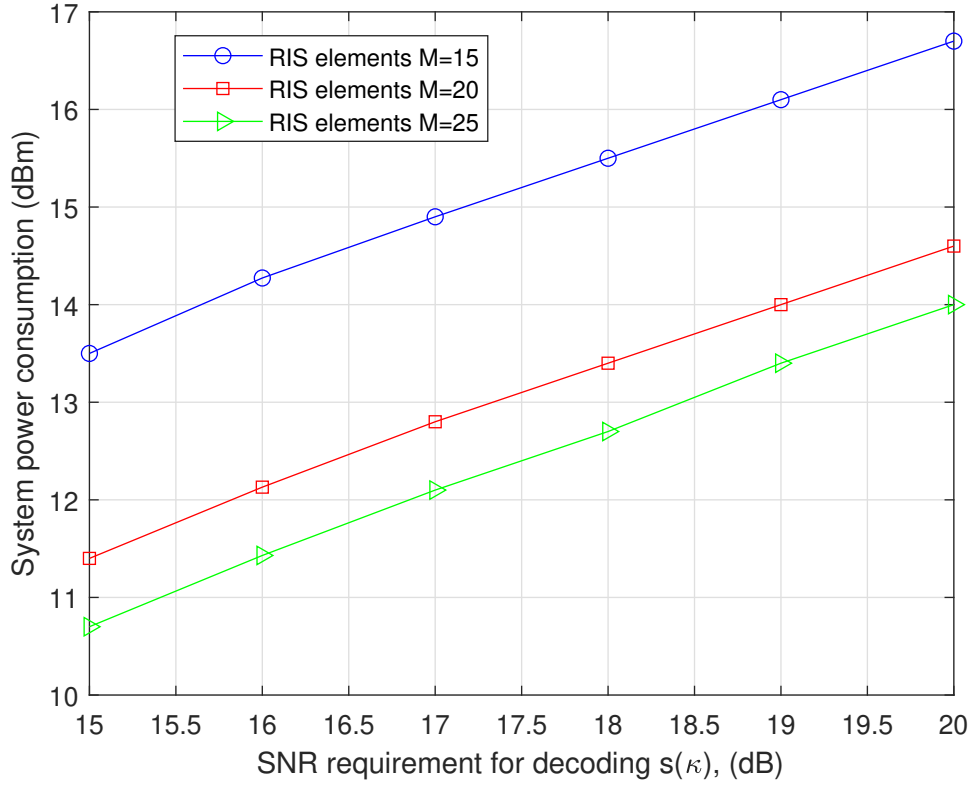


Figure 2.8: Power consumption vs SNR requirement for decoding $s(\kappa)$.

Figure 2.9 depicts the power consumption as the distance between the RIS and the SU varies, with $\Psi_v = 65$ and $N = 16$. It can be observed that when the distance is very short (e.g., 1 meter), the performance of both active and passive RIS is nearly identical for the two CSI error models. However, as the distance increases, active RIS demonstrates superior performance compared to passive RIS.

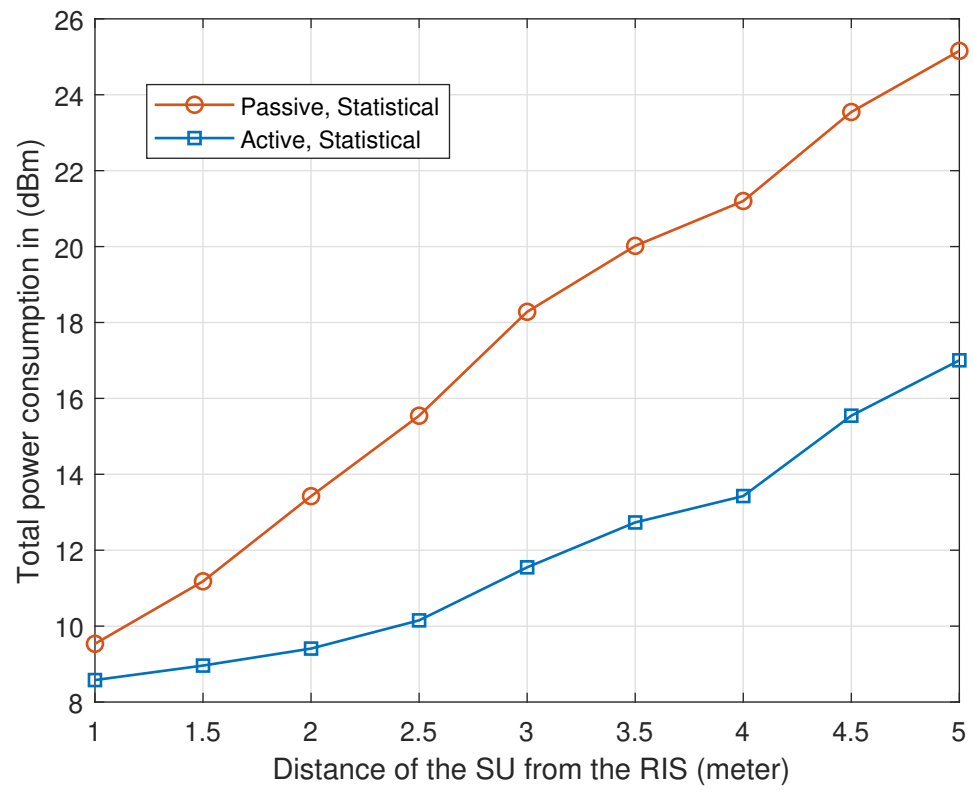


Figure 2.9: Power consumption vs distance of the SU from RIS in meters.

2.6 Conclusions

In this chapter, the power consumption problem of a multicast communication system in SR assisted by an active RIS has been solved under two types of CSI error models for the eavesdroppers. The problem was formulated as minimizing the total system power (including both PTx and active RIS power), subject to QoS and security constraints. Given the non-convex nature of the problem, optimizing both transmit and reflection beamforming vectors was challenging. To address this, AO was proposed to iteratively solve the problem, reaching a suboptimal solution. The SDR technique was employed in each subproblem to facilitate the solution. The channel uncertainties associated with the two types of EVs were handled using the S-Procedure for the bounded CSI error model and Bernstein-Type Inequality for the statistical CSI error model. Finally, simulation results were conducted to validate the effectiveness of the proposed solution.

CHAPTER 3

MULTI-USER BEAMFORMING

In this chapter, a new optimization problem where now the PTx transmits different messages for different users by means of multi-beamforming optimization is introduced. This new problem is more challenging due to the included interference, especially in the presence of SR communication as well as the existence of the different types of eavesdroppers. The following sections define the system model with the signal model and problem formulation, then the proposed solution as well as the simulation results and conclusion.

The same system model components will be used in this section too as in Chapter 2 Fig. 2.1. The difference now is that in Chapter 2, the system was multicast beamforming (i.e., the same signal transmitted to all PUs), while now the PTx tends to transmit different signals to each PU by means of multi-user beamforming. For consistency, the same notations of the channels as in Table 1.2 used in Chapter 2 will be used here.

3.1 Signal Model

The signal model now will include the effect of multi-user beamforming where the interference will be included too. The received signal at the j^{th} PU for decoding $\mathbf{s}_j(\kappa)$ during one secondary symbol period can be written as

$$\begin{aligned} y_{p,j}(\kappa) = & \mathbf{h}_{p,j}^H \mathbf{f}_j \mathbf{s}_j(\kappa) + \sum_{j' \in \mathcal{J} \setminus \{j\}} \mathbf{h}_{p,j}^H \mathbf{f}_{j'} \mathbf{s}_{j'}(\kappa) + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{f}_j \mathbf{s}_j(\kappa) \\ & + \sum_{j' \in \mathcal{J} \setminus \{j\}} \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{f}_{j'} \mathbf{s}_{j'}(\kappa) + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{n}_{RIS}(\kappa) + n_j(\kappa), \quad \kappa \in \mathcal{K}, j \in \mathcal{J} \end{aligned} \quad (3.1)$$

where $\kappa \in \mathcal{K}$ and $\mathcal{K} = \{1, \dots, K\}$ is the set of all primary symbol, $\mathbf{f}_j \in \mathbb{C}^{M \times 1}$, $\mathbf{F} = [\mathbf{f}_1, \dots, \mathbf{f}_J] \in \mathbb{C}^{M \times J}$, $\mathbf{\Theta} \in \mathbb{C}^{N \times N}$ which includes the diagonal elements of the RIS, $\mathbf{n}_{RIS}(\kappa) \sim \mathcal{CN}(\mathbf{0}, \sigma_{RIS}^2 \mathbf{I}_N)$, and $n_j(\kappa) \sim \mathcal{CN}(\mathbf{0}, \sigma_j^2)$. Then the instantaneous SNR for decoding $\mathbf{s}_i(\kappa)$ at the j^{th} PU for fixed v can be as the following

$$\bar{\Psi}_{p,j} = \frac{|\left(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{H}_{(P,RIS)}\right) \mathbf{f}_j|^2}{\sum_{j' \in \mathcal{J} \setminus \{j\}} \left|\left(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H(v\mathbf{\Theta}) \mathbf{H}_{(P,RIS)}\right) \mathbf{f}_{j'}\right|^2 + \sigma_j^2 + \sigma_{RIS}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta} v\|^2} \quad (3.2)$$

since v is modulated using BPSK at the RIS, the average SINR for the j^{th} PU can be expressed as follows

$$\begin{aligned}
\Psi_{p,j} &= \mathbb{E} [\bar{\Psi}_{p,j}] = \\
&\frac{|(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sum_{j' \in \mathcal{J} \setminus \{j\}} |(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2 \right)} \\
&+ \frac{|(\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sum_{j' \in \mathcal{J} \setminus \{j\}} |(\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2 \right)}, \quad j \in \mathcal{J}
\end{aligned} \tag{3.3}$$

It is clear that the SNR equation will be very complex due to the interference terms, therefore the term signal-to-interference noise ratio (SINR) will be used in this chapter. For the SU, similarly, the received signal at the SU will be written as

$$\begin{aligned}
y_s(k) &= \sum_{j \in \mathcal{J}} \mathbf{h}_s^H \mathbf{f}_j \mathbf{s}_j(k) + \sum_{j \in \mathcal{J}} \mathbf{g}_s^H (v \mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{f}_j \mathbf{s}_j(k) + \mathbf{g}_s^H (v \mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{n}_{\text{RIS}}(k) + n_s(k), \\
&\quad k \in \mathcal{K}, j \in \mathcal{J}
\end{aligned} \tag{3.4}$$

where $n_s(k) \sim \mathcal{CN}(\mathbf{0}, \sigma_s^2)$ is the AWGN at the SU receiver. The maximum likelihood detection can be used to jointly decode both $\mathbf{s}_j(\kappa)$ of each PU's message one by one and v [17]. Therefore, we can write the average SNR for decoding $s_j(\kappa)$ at the SU as follows

$$\begin{aligned}
\Psi_s^{s,j} &= \\
&\frac{|(\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sum_{j'=j+1, \dots, J} |(\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2 \right)} \\
&+ \frac{|(\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sum_{j'=j+1, \dots, J} |(\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2 \right)}, \quad j \in \mathcal{J}
\end{aligned} \tag{3.5}$$

After getting the $s_j(\kappa)$ for all $j \in \mathcal{J}$, SIC can be used to remove the direct link, i.e., the PT-SU link. Therefore, the remaining signal can be represented in the sense of the secondary symbol period. Let's denote it as $\tilde{y}_s$, where

$$\begin{aligned} \tilde{y}_s = \sum_{j=1, \dots, J} [\tilde{y}_{s_j}(1), \dots, \tilde{y}_{s_j}(K)] &= \sum_{j=1, \dots, J} \mathbf{g}_s^H(v\mathbf{\Theta})\mathbf{H}_{(P, RIS)}\mathbf{f}_j[s_j(1), \dots, s_j(K)]^T \\ &\quad + \mathbf{g}_s^H(v\mathbf{\Theta})[n_{RIS}(1), \dots, n_{RIS}(K)]^T \\ &\quad + [n_s(1), \dots, n_s(K)]^T. \end{aligned} \quad (3.6)$$

By using the MRC technique [3], the average SNR for decoding v at the SU is approximately equal to [31]

$$\Psi_s^v \approx \frac{K \sum_{j \in \mathcal{J}} |(\mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P, RIS)}) \mathbf{f}_j|^2}{\sigma_s^2 + \sigma_{RIS}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2}. \quad (3.7)$$

For the case of the two types of eavesdroppers, we are assuming the worst-case scenario, in other words, we are assuming each eavesdropper has a powerful SIC that can eliminate the interference from different users when trying to decode the information of one PU. Under this assumption, the received signal at the l^{th} EVs-I is as follows

$$\begin{aligned} y_{l,j}(\kappa) &= \mathbf{h}_{e1,l}^H \mathbf{f}_j \mathbf{s}_j(\kappa) + \mathbf{g}_{e1,l}^H(v\mathbf{\Theta})\mathbf{H}_{(P, RIS)}\mathbf{f}_j \mathbf{s}_j(\kappa) \\ &\quad + \mathbf{g}_{e1,l}^H(v\mathbf{\Theta})\mathbf{n}_{RIS}(\kappa) + n_l(\kappa), \quad \kappa \in \mathcal{K}, j \in \mathcal{J}, l \in \mathcal{L} \end{aligned} \quad (3.8)$$

where the interference contributions from other users do not appear in the equation due to the ability to eliminate this interference.

Therefore, the SNR at the l^{th} EVs-I can now be written as

$$\begin{aligned}\Psi_{l,j} &= \mathbb{E} [\bar{\Psi}_{l,j}] = \\ &= \frac{|(\mathbf{h}_{e1,l}^H + \mathbf{g}_{e1,l}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sigma_{e1,l}^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{e1,l}^H \mathbf{\Theta}\|^2 \right)} + \frac{|(\mathbf{h}_{e1,l}^H - \mathbf{g}_{e1,l}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sigma_{e1,l}^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{e1,l}^H \mathbf{\Theta}\|^2 \right)}, \quad j \in \mathcal{J}, l \in \mathcal{L}\end{aligned}\quad (3.9)$$

The received signal at EVs-II can be written as

$$y_{e2}(\kappa) = \sum_{j \in \mathcal{J}} \mathbf{h}_{e2}^H \mathbf{f}_j \mathbf{s}_j(k) + \sum_{j \in \mathcal{J}} \mathbf{g}_{e2}^H (v \mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{f}_j \mathbf{s}_j(k) + \mathbf{g}_{e2}^H (v \mathbf{\Theta}) \mathbf{H}_{(P,RIS)} \mathbf{n}_{\text{RIS}}(k) + n_{e2}(k),$$

$$\kappa \in \mathcal{K}, j \in \mathcal{J} \quad (3.10)$$

This eavesdropper type targets the signal v transmitted to the SU from the RIS. Therefore, it needs to decode $s_j(k)$ for $j \in \mathcal{J}$ one by one to be able to decode the signal v . As a result, the average SNR for decoding $s_j(k)$ can be formulated as follows considering the worst-case scenario where these EVs also can eliminate the interference terms.

$$\begin{aligned}\Psi_j^{e2} &= \mathbb{E} [\bar{\Psi}_j^{e2}] = \\ &= \frac{|(\mathbf{h}_{e2}^H + \mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sigma_{e2}^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2 \right)} + \frac{|(\mathbf{h}_{e2}^H - \mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{2 \left(\sigma_{e2}^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2 \right)}, \quad j \in \mathcal{J}\end{aligned}\quad (3.11)$$

Utilizing the MRC technique [3], the average SNR for decoding v at the EVs-II is approximately equal to [31]:

$$\Psi_{e2}^v \approx \frac{K \sum_{j \in \mathcal{J}} |(\mathbf{g}_{e2}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{f}_j|^2}{\sigma_{e2}^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{e2}^H \mathbf{\Theta}\|^2}. \quad (3.12)$$

In this chapter, the same CSI uncertainty models used in Chapter 2 will be

used here as in Section 2.2. Also, refer back to Table 1.2 for channel descriptions of the system.

3.2 Power Consumption

3.2.1 Active RIS

Due to the existence of active RIS, the total power consumption can be calculated as follows

$$P_{total} = P_{PT} + P_{active,RIS} - P_{incident} \quad (3.13)$$

where $P_{PTx} = \sum_{j=1,\dots,J} \|\mathbf{f}_j\|^2$, $\forall j \in \mathcal{J}$ represents the transmit power from the PTx, $P_{incident} = \sum_{j=1,\dots,J} \|\mathbf{H}_{(P, RIS)} \mathbf{f}_j\|^2$, $\forall j \in \mathcal{J}$. Similarly, the power consumption of active RIS can be calculated for N reflecting elements as in [37],

$$P_{active, RIS} = N(P_{SW} + P_{DC}) + \sum_{j=1,\dots,J} [\|\boldsymbol{\Theta} \mathbf{H}_{(P, RIS)} \mathbf{f}_j\|^2] + \sigma_{RIS}^2 \|\boldsymbol{\Theta}\|^2 \quad (3.14)$$

where P_{DC} is the direct current biasing power at each RIS element, P_{SW} is the switch and control power of each RIS element, and $\sum_{j=1,\dots,J} [\|\boldsymbol{\Theta} \mathbf{H}_{(P, RIS)} \mathbf{f}_j\|^2] + \sigma_{RIS}^2 \|\boldsymbol{\Theta}\|^2$ represents the output power of the active RIS [9].

3.2.2 Passive RIS

The passive RIS has been considered as a benchmark scheme in this thesis. The total power consumption in the passive RIS case can be calculated as in [26]

$$P_{total} = P_{PT} + P_{passive,RIS} \quad (3.15)$$

For the circuit power of the passive RIS, it can be expressed as

$$P_{\text{passive}, RIS} = N(P_{\text{SW}}) \quad (3.16)$$

Because the RIS is passive, the noise power is typically neglected.

3.3 Problem Formulation and Proposed Solution

This section introduces the problem formulation under the two CSI error models, starting with the bounded and statistical, respectively.

3.3.1 Bounded CSI Error Model

In this subsection, the problem formulation under the bounded uncertainty is proposed as follows

$$\begin{aligned}
& \min_{\mathbf{f}, \boldsymbol{\Theta}} \quad \sum_{j=1, \dots, J} \|\mathbf{f}_j\|^2 + N(P_{\text{SW}} + P_{\text{DC}}) + \sum_{j=1, \dots, J} \|\boldsymbol{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2 + \sigma_{\text{RIS}}^2 \|\boldsymbol{\Theta}\|^2 - \sum_{j=1, \dots, J} \|\mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2 \\
& \text{s.t.} \\
& \text{C1: } \Psi_{p,j}^s \geq \Psi_{\mathbf{s}_j(\kappa)}, \quad j \in \mathcal{J}, \\
& \text{C2: } \Psi_s^{s,j} \geq \Psi_{\mathbf{s}_j(\kappa)}, \quad j \in \mathcal{J}, \\
& \text{C3: } \Psi_S^v \geq \Psi_v, \\
& \text{C4: } \Psi_{l,j} \leq \Psi_{\text{EVS-I}}, \\
& \quad \|\Delta \mathbf{h}_{e1,l}\|_2 \leq \beta_{h,l}, \quad \|\Delta \mathbf{g}_{e1,l}\|_2 \leq \beta_{g,l}, \quad l \in \mathcal{L}, \quad j \in \mathcal{J}, \\
& \text{C5: } \Psi_{e2}^v \leq \Psi_{\text{EVS-II}}, \\
& \quad \|\Delta \mathbf{h}_{e2}\|_2 \leq \beta_{h,e2}, \quad \|\Delta \mathbf{g}_{e2}\|_2 \leq \beta_{g,e2}, \\
& \text{C6: } 0 \leq a_n \leq \rho, \quad 0 \leq \phi_n \leq 2\pi, \quad n \in N, \quad (\mathbf{P1})
\end{aligned}$$

where $\Psi_{\mathbf{s}_j(\kappa)}$, Ψ_v , $\Psi_{\text{EVS-I}}$, and $\Psi_{\text{EVS-II}}$ are the decoding SNR of the primary transmission user j^{th} , the decoding SNR of the secondary transmission, the maximum SNR threshold at EVs-I for decoding j^{th} PU information and the maximum SNR threshold at EVs-II to decode the SU's signal, respectively. C1 sets the minimum SNR at the PU to decode $\mathbf{s}_j(\kappa)$, C2 and C3 guarantee the minimum SINR level at the SU to first decode $\mathbf{s}_j(\kappa)$ and then uses the SIC technique to decode v . Constraint C4 is used to ensure a secure transmission toward the PUs by setting the maximum SINR gained at EVs-I to be lower than the SINR required to decode $\mathbf{s}_j(\kappa)$, $\forall j$ under the bounded CSI error model. C5 controls the maximum SINR achieved at the EVs-II attempting to decode the SU's message v . Constraint C6 is related to the reflection parameters of the active RIS.

The problem in (P1) is a non-convex and not easy to deal with even if we divided the problem into two subproblems similar to Chapter 2 where optimizing the transmit beamforming matrix $\mathbf{F}$ and the reflection beamforming vector Θ is done separately. This is due to the interference summation at the denominator which makes the SINR equations have no common denominator because of the averaging over $v = \{1, -1\}$. To tackle this challenge, each SINR of the PUs and SU can be divided into two parts, one when $v = 1$ and another one when $v = -1$, and solve three subproblems alternately. In subproblem 1, the transmit beamforming matrix $\mathbf{F}$ is optimized for a given initial values for the reflection beamforming vector Θ and the different thresholds of each part of the constraints. Subproblem 2 optimizes the reflection beamforming vector Θ given the transmit beamforming matrix $\mathbf{F}$ obtained from subproblem 1 and also the same thresholds. In subproblem 3, the different thresholds are updated.

Transmit Beamforming Optimization

In this subproblem, the transmit beamforming matrix $\mathbf{F}$ is optimized given Θ , and the different thresholds (i.e., UP_j^+ , UP_j^- , US_j^+ , US_j^-), these thresholds are needed to separate C1, C2, and C3 constraints each into two parts (i.e., positive when $v = 1$ and negative when $v = -1$). In the first iteration these thresholds are initialized as $\Psi_{s(\kappa)}/2$ for each one. On the other hand, for constraints C4, and C5, there is no need to separate the negative and positive parts of the constraints in which the original thresholds will be used since we are considering the optimization at the worst-case scenario where EVs can eliminate interference.

To tackle the uncertainty of the channels related to the two types of EVs, the same **Lemma 1** in Section 2.4.1 in Chapter 2 will be used. To convert problem

P1 to a form suitable to be solved, an auxiliary variable has been introduced for each user beamforming vector such $\mathbf{F}_j = \mathbf{f}_j \mathbf{f}_j^H, \forall j \in \mathcal{J}$ where $\text{Rank}(\mathbf{F}_j) = 1$ and $\mathbf{F}_j \succeq \mathbf{0}$. As a result, constraints C1, C2 and C3 can be reformulated as

$$\begin{aligned} \text{C8a: } & \text{Tr} \left(\left((\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j (\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right) \geq \\ & 2UP_j^+ \left(z_j + \sum_{j' \in \mathcal{J} \setminus \{j\}} \text{Tr} \left((\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_{j'} (\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right), j \in \mathcal{J}, \\ \text{C8b: } & \text{Tr} \left(\left((\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j (\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right) \geq \\ & 2UP_j^- \left(z_j + \sum_{j' \in \mathcal{J} \setminus \{j\}} \text{Tr} \left((\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_{j'} (\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right), j \in \mathcal{J}, \end{aligned}$$

Similarly, for the SU constraint C2 can be reformulated as

$$\begin{aligned} \text{C9a: } & \text{Tr} \left(\left((\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j (\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right) \geq \\ & 2US_j^+ \left(z_s + \sum_{j'=j+1, \dots, \mathcal{J}} \text{Tr} \left((\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_{j'} (\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right), j \in \mathcal{J}, \\ \text{C9b: } & \text{Tr} \left(\left((\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j (\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right) \geq \\ & 2US_j^- \left(z_s + \sum_{j'=j+1, \dots, \mathcal{J}} \text{Tr} \left((\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_{j'} (\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H \right) \right), j \in \mathcal{J}, \end{aligned}$$

$$\text{C10: } K \sum_{j=1, \dots, \mathcal{J}} \text{Tr}(\mathbf{H}_{(P,RIS,SU)} \mathbf{F}_j) \geq \Psi_v (\sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2)$$

where

$$\mathbf{H}_{(P,RIS,SU)} = (\mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)})^H (\mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P,RIS)}),$$

$$z_j = \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2 \text{ and } z_s = \sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2.$$

For C4, and C5, the S-Procedure in **Lemma 1** in Section 2.4.1 in Chapter 2 will be used to equivalently consider the uncertainties in the estimation error of the channels, after reformulating them as follows,

For C4,

$$\Delta \mathbf{x}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} + \Delta \mathbf{x}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} + \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j A_1 \Delta \mathbf{x}_{e1,l} + \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} \leq \Psi_{EVS-1} \sigma_{e1,l}^2, \quad (3.17)$$

$$\|\Delta \mathbf{x}_{e1,l}\|^2 \leq \beta_{h,l}^2 + \beta_{g,l}^2, l \in \mathcal{L}, j \in \mathcal{J},$$

where

$$\tilde{\mathbf{F}}_j = \begin{bmatrix} \mathbf{\Theta} \mathbf{H}_{(P,RIS)} \mathbf{F}_j \mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H - \Psi_{EVS-1} \sigma_{RIS}^2 \mathbf{\Theta} \mathbf{\Theta}^H & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_j \end{bmatrix}$$

$$\mathbf{x}_{e1,l} = \begin{pmatrix} \mathbf{g}_{e1,l} \\ \mathbf{h}_{e1,l} \end{pmatrix}, \quad \hat{\mathbf{x}}_{e1,l} = \begin{pmatrix} \hat{\mathbf{g}}_{e1,l} \\ \hat{\mathbf{h}}_{e1,l} \end{pmatrix}, \quad \Delta \mathbf{x}_{e1,l} = \begin{pmatrix} \Delta \mathbf{g}_{e1,l} \\ \Delta \mathbf{h}_{e1,l} \end{pmatrix}.$$

Therefore, the equivalent LMI can be formulated for $l \in \mathcal{L}$ decoding j^{th} PU as follows

$$\nu_{l,j} \begin{bmatrix} \mathbf{I}_{N+M} & \mathbf{0} \\ \mathbf{0} & -\beta_{e1,l}^2 \end{bmatrix} \succeq \begin{bmatrix} \tilde{\mathbf{F}}_j & \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} \\ \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j & \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} - \Psi_{EVS-1} - \sigma_{e1,l}^2 \end{bmatrix}, \quad l \in \mathcal{L}, j \in \mathcal{J}, \quad (3.18)$$

where $\nu_{l,j} \geq 0$ is a slack variable for the l^{th} EVS-I and needs to be optimized in accordance with the

$$\beta_{e1,l}^2 = \beta_{h,l}^2 + \beta_{g,l}^2.$$

We can notice that (3.18) is derived from (3.17) by replacing Lemma 1 as follows,

$$x = \Delta \mathbf{x}_{e1,l}, \quad A_1 = I_{M+N}, \quad u_1 = \mathbf{0}, \quad u_2 = \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l}, \quad a_1 = -\beta_{e1,l}^2,$$

$$A_2 = \tilde{\mathbf{F}}_j, \quad a_2 = \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} - \Psi_{EVS-1} \sigma_{e1,l}^2.$$

Then C4 constraint can be rewritten as

$$\mathbf{C11:} LMI_{e1,l}^{\mathbf{F}_j} = \begin{bmatrix} \nu_{l,j} I_{N+M} - \tilde{\mathbf{F}}_j & -\tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} \\ -\hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j & -\nu_{l,j} \beta_{e1,l}^2 - \hat{\mathbf{x}}_{e1,l}^H \tilde{\mathbf{F}}_j \hat{\mathbf{x}}_{e1,l} + \Psi_{\text{EVs-I}} - \sigma_{e1,l}^2 \end{bmatrix} \succeq \mathbf{0}, \quad l \in \mathcal{L}, j \in \mathcal{J},$$

where $LMI_{e1,l}^{\mathbf{F}_j} \in \mathbb{C}^{(N+M+1) \times (N+M+1)}$. Similarly, for constraint C5, by using the same principle as in equation (3.17),

$$\Delta \mathbf{x}_{e2}^H \tilde{\mathbf{F}}_{e2} \Delta \mathbf{x}_{e2} + \Delta \mathbf{x}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} + \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \Delta \mathbf{x}_{e2} + \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} \leq \Psi_{EVsII} \sigma_{e2}^2, \|\Delta \mathbf{x}_{e2}\|^2 \leq \beta_{g,e2}^2 \quad (3.19)$$

where $\mathbf{x}_{e2} = \mathbf{g}_{e2}$, $\hat{\mathbf{x}}_{e2} = \hat{\mathbf{g}}_{e2}$, $\Delta \mathbf{x}_{e2} = \Delta \mathbf{g}_{e2}$, this is because the SNR for decoding the v at the EVs-II only depends on the uncertainty of the channel related to the RIS-EVs-II. The LMI for this type of Eavesdroppers would be as follows

$$\nu_{e2} \begin{bmatrix} \mathbf{I}_N & \mathbf{0} \\ \mathbf{0} & -\beta_{e2}^2 \end{bmatrix} \succeq \begin{bmatrix} \tilde{\mathbf{F}}_{e2} & \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} \\ \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} & \hat{\mathbf{x}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{x}}_{e2} - \frac{1}{K} \Psi_{EVsII} \sigma_{e2}^2 \end{bmatrix} \quad (3.20)$$

where

$$\tilde{\mathbf{F}}_{e2} = \sum_{j, \dots, J} \mathbf{\Theta} \mathbf{H}_{(\text{P,RIS})} \mathbf{F}_j \mathbf{H}_{(\text{P,RIS})}^H \mathbf{\Theta}^H - \frac{1}{K} \Psi_{EVsII} \sigma_{\text{RIS}}^2 \mathbf{\Theta} \mathbf{\Theta}^H,$$

Now the LMI for approximating C5 can be expressed as

C12:

$$LMI_{e2}^F = \begin{bmatrix} \nu_{e2} I_N - \tilde{\mathbf{F}}_{e2} & -\tilde{\mathbf{F}}_{e2} \hat{\mathbf{g}}_{e2} \\ -\hat{\mathbf{g}}_{e2}^H \tilde{\mathbf{F}}_{e2} & -\nu_{e2} \beta_{e2}^2 - \hat{\mathbf{g}}_{e2}^H \tilde{\mathbf{F}}_{e2} \hat{\mathbf{g}}_{e2} + \frac{1}{K} \Psi_{EVsII} \sigma_{e2}^2 \end{bmatrix} \succeq \mathbf{0},$$

where $LMI_{e2}^F \in \mathbb{C}^{(N+1) \times (N+1)}$

Then, the new subproblem for optimizing F can be written as

$$\begin{aligned}
& \min_{\mathbf{F}, \nu_{l,j}, \nu_{e2,j}} \sum_{j=1, \dots, J} [\text{Tr}(\mathbf{F}_j) + \text{Tr}((\mathbf{H}_{(P,RIS)}^H \boldsymbol{\Theta}^H \boldsymbol{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j) - \text{Tr}((\mathbf{H}_{(P,RIS)}^H \mathbf{H}_{(P,RIS)}) \mathbf{F}_j)] \\
& \text{s.t.} \quad C8, C9, C10, C11, C12 \\
& \quad C13 : \text{Rank}(\mathbf{F}_j) = 1 \\
& \quad C14 : \mathbf{F}_j \succeq \mathbf{0} \tag{P2}
\end{aligned}$$

P2 is still non-convex due to constraint C14. After relaxing C14 by using SDR methods, P2 can be reformulated as in (P3).

$$\begin{aligned}
& \min_{\mathbf{F}, \nu_{l,j}, \nu_{e2,j}} \sum_{j=1, \dots, J} [\text{Tr}(\mathbf{F}_j) + \text{Tr}((\mathbf{H}_{(P,RIS)}^H \boldsymbol{\Theta}^H \boldsymbol{\Theta} \mathbf{H}_{(P,RIS)}) \mathbf{F}_j) - \text{Tr}((\mathbf{H}_{(P,RIS)}^H \mathbf{H}_{(P,RIS)}) \mathbf{F}_j)] \\
& \text{s.t.} \quad C8, C9, C10, C11, C12, C14 \tag{P3}
\end{aligned}$$

P3 can be efficiently solved for each $j \in \mathcal{J}$ as it is transformed into a relaxed semidefinite programming (SDP) problem, which can be addressed using techniques such as the interior-point method. Simulation results demonstrate that the suboptimal $\mathbf{F}_j^*$ for $j \in \mathcal{J}$ consistently achieves a rank-one solution. To ensure the algorithm always yields a rank-one solution, Gaussian randomization is applied in cases where the subproblem does not result in a rank-one matrix. The eigenvalue decomposition is then used to extract the suboptimal beamforming vector, $\mathbf{f}_j^{*(t)}$, at the t^{th} iteration for all $j \in \mathcal{J}$ [31].

Reflection Beamforming Optimization

After getting the $\mathbf{F}_j^{(t)}$ for $j \in \mathcal{J}$, we optimized Θ while fixing $\mathbf{F}_j$. Assume $\mathbf{p} = [p_1, \dots, p_N]^T$ to be the vector of the diagonal elements of the matrix Θ , by introducing a similar variable $\mathbf{P} = \mathbf{p}\mathbf{p}^H$, $\mathbf{P} \succeq 0$, $\text{Rank}(\mathbf{P}) = 1$, $P(n, n) \leq \rho^2$, $n \in \mathcal{N}$. Then, C1, C2, and C3 can be rewritten as follows

C15a:

$$\begin{aligned} & \frac{1}{2} \left[\text{Tr}(\mathbf{H}_{p,j} \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_j)(\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_j \text{UP}_j^+ \geq \\ & \text{UP}_j^+ \left(\sigma_j^2 + \sum_{j' \in \mathcal{J} \setminus \{j\}} [\text{Tr}(\mathbf{h}_{p,j} \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j'})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_{j'}) (\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}] \right), \\ & j \in \mathcal{J}. \end{aligned}$$

C15b:

$$\begin{aligned} & \frac{1}{2} \left[\text{Tr}(\mathbf{H}_{p,j} \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_j)(\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_j \text{UP}_j^- \geq \\ & \text{UP}_j^- \left(\sigma_j^2 + \sum_{j' \in \mathcal{J} \setminus \{j\}} [\text{Tr}(\mathbf{h}_{p,j} \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j'})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_{j'}) (\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}] \right), j \in \mathcal{J}. \end{aligned}$$

where $\mu_j = \sigma_{\text{RIS}}^2 \mathbf{g}_{p,j}^H \mathbf{P} \mathbf{g}_{p,j}$, $\mathbf{H}_{(\text{P, RIS, PU, j})} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H \mathbf{g}_{p,j} \mathbf{g}_{p,j}^H \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)$

and $\mathbf{H}_{(\text{P, RIS, PU, j'})} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H \mathbf{g}_{p,j} \mathbf{g}_{p,j}^H \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})$. C2 can also be

reformulated as follows

C16a:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_s \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, SU, j})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_j)(\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_s \text{US}_j^+ \geq$$

$$\text{US}_j^+ \left(\sigma_s^2 + \sum_{j'=j+1, \dots, J} [\text{Tr}(\mathbf{H}_s \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, SU, j'})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_{j'}) (\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}] \right),$$

C16b:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_s \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_j)(\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_s \text{US}_j^- \geq$$

$$\text{US}_j^- \left(\sigma_s^2 + \sum_{j'=j+1, \dots, J} [\text{Tr}(\mathbf{H}_s \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, SU, j'})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_{j'}) (\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}] \right),$$

C17: $K \sum_{j=1, \dots, J} \text{Tr}(\mathbf{H}_{(\text{P, RIS, SU, j})} \mathbf{P}) - \mu_s \Psi_v \geq \Psi_v (\sigma_s^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2)$, where

$\mu_s = \sigma_{\text{RIS}}^2 \mathbf{g}_s^H \mathbf{P} \mathbf{g}_s$, $\mathbf{H}_{(\text{P, RIS, SU, j})} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H \mathbf{g}_s \mathbf{g}_s^H \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)$ and

$\mathbf{H}_{(\text{P, RIS, SU, j'})} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H \mathbf{g}_s \mathbf{g}_s^H \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})$. Similarly, the S-

Procedure is used to deal with constraints C4, and C5.

For C4, $\overline{\mathbf{P}}_j$ is defined as

$$\overline{\mathbf{P}}_j = \begin{bmatrix} \text{diag}(\mathbf{H}_{(\text{P, RIS})} \mathbf{f}_j) \mathbf{P} \text{diag}(\mathbf{H}_{(\text{P, RIS})} \mathbf{f}_j)^H - \sigma_{\text{RIS}}^2 \Psi_{\text{EVS}-I} \mathbf{P} & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_j \end{bmatrix}.$$

Which gives the new formulation of C4 as

$$\mathbf{C18: LMI}_{\mathbf{P}}^{l,j} = \begin{bmatrix} \overline{\nu}_{l,j} \mathbf{I}_{N+M} - \overline{\mathbf{P}}_j & -\overline{\mathbf{P}}_j \hat{\mathbf{x}}_l \\ -\hat{\mathbf{x}}_l^H \overline{\mathbf{P}}_j & -\overline{\nu}_l \beta_{e1,l}^2 - \hat{\mathbf{x}}_l^H \overline{\mathbf{P}}_j \hat{\mathbf{x}}_l + \Psi_{\text{EVS}-I} \sigma_{e1,l}^2 \end{bmatrix} \succeq \mathbf{0}, \quad l \in \mathcal{L}, j \in \mathcal{J},$$

Similarly, for C5 constraints,

$$\mathbf{C19:LMIP}^{e2} = \begin{bmatrix} \bar{\nu}_{e2}\mathbf{I}_N - \bar{\mathbf{P}}_{e2} & -\bar{\mathbf{P}}_{e2}\hat{\mathbf{x}}_{e2} \\ -\hat{\mathbf{x}}_{e2}^H\bar{\mathbf{P}}_{e2} & -\bar{\nu}_{e2}\beta_{o,2}^2 - \hat{\mathbf{x}}_{e2}^H\bar{\mathbf{P}}_{e2}\hat{\mathbf{x}}_{e2} + \frac{1}{K}\Psi_{\text{EVS-II}}\sigma_{e2}^2 \end{bmatrix} \succeq \mathbf{0},$$

where

$$\bar{\mathbf{P}}_{e2} = \sum_{j=1,\dots,J} [\text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f}_j)\mathbf{P}\text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f}_j)^H] - \sigma_{\text{RIS}}^2 \frac{1}{K}\Psi_{\text{EVS-II}}\mathbf{P}.$$

Therefore, the subproblem to optimize the $\mathbf{P}$ can be reformulated as

$$\min_{\mathbf{P}, \bar{\nu}_{l,j}, \bar{\nu}_{e2}} \sum_{j=1,\dots,J} [\text{Tr}(\text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f}_j)\text{diag}(\mathbf{H}_{(\mathbf{P},\text{RIS})}\mathbf{f}_j)^H\mathbf{P})] + \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P})$$

subject to

$$\text{C15, C16, C17, C18, C19,}$$

$$\text{C20: Rank}(\mathbf{P}) = 1$$

$$\text{C21: } \mathbf{P} \succeq \mathbf{0}$$

$$\text{C22: } P(n, n) \leq \rho^2, n \in \mathcal{N} \quad (\text{P4})$$

P4 is still a non-convex problem due to the rank-one constraint (i.e., C20). After dropping C20, the problem can be solved using CVX solver (i.e., SDP). The objective function in P4 is very small as compared to the AO tolerance for convergence. For better convergence of the algorithm, we can introduce the SNR residuals for C15, and C16 constraints, and the problem can be converted to a maximization

one as in P5.

$$\max_{\mathbf{P}, \bar{\nu}_{l,j}, \bar{\nu}_{e2}, \gamma^p, \gamma^n} - \sum_{j=1, \dots, J} [\text{Tr}(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j)^H \mathbf{P})] - \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P}) + \sum_{j=1}^{2J} \gamma_j^p + \sum_{j=1}^{2J} \gamma_j^n$$

s.t.

$\overline{\text{C15a}}$:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_{p,j} \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_j)(\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_j \text{UP}_j^+ - \gamma_j^p \sigma_j^2 \geq \text{UP}_j^+ \left(\sigma_j^2 + \text{INT}_j \right), j \in \mathcal{J}.$$

where

$$\text{INT}_j = \sum_{j' \in \mathcal{J} \setminus \{j\}} [\text{Tr}(\mathbf{h}_{p,j} \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j'})} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_{j'}) (\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}],$$

$\overline{\text{C15b}}$:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_{p,j} \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_j)(\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H\} \right] - \mu_j \text{UP}_j^- - \gamma_j^n \sigma_j^2 \geq \text{UP}_j^- \left(\sigma_j^2 + \text{INT}'_j \right), j \in \mathcal{J}.$$

where

$$\text{INT}'_j = \sum_{j' \in \mathcal{J} \setminus \{j\}} [\text{Tr}(\mathbf{h}_{p,j} \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(\text{P, RIS, PU, j'})} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_{p,j}^H \mathbf{f}_{j'}) (\mathbf{g}_{p,j}^H \mathbf{P} \mathbf{H}_{(P, \text{RIS})} \mathbf{f}_{j'})^H\}],$$

$\overline{C16a}$:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_s \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(P, RIS, SU, j)} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_j)(\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, RIS)} \mathbf{f}_j)^H\} \right] - \mu_s \text{US}_j^+ - \gamma_{(J+j)}^p \sigma_s^2 \geq$$

$$\text{US}_j^+ \left(\sigma_s^2 + \sum_{j'=j+1, \dots, J} [\text{Tr}(\mathbf{H}_s \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(P, RIS, SU, j')} \mathbf{P}) + 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_{j'}) (\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, RIS)} \mathbf{f}_{j'})^H\}] \right), j \in \mathcal{J}.$$

$\overline{C16b}$:

$$\frac{1}{2} \left[\text{Tr}(\mathbf{H}_s \mathbf{F}_j) + \text{Tr}(\mathbf{H}_{(P, RIS, PU, j)} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_j)(\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, RIS)} \mathbf{f}_j)^H\} \right] - \mu_s \text{US}_j^- - \gamma_{(J+j)}^n \sigma_s^2 \geq$$

$$\text{US}_j^- \left(\sigma_s^2 + \sum_{j'=j+1, \dots, J} [\text{Tr}(\mathbf{H}_s \mathbf{F}_{j'}) + \text{Tr}(\mathbf{H}_{(P, RIS, PU, j')} \mathbf{P}) - 2\text{Re}\{(\mathbf{h}_s^H \mathbf{f}_{j'}) (\mathbf{g}_s^H \mathbf{P} \mathbf{H}_{(P, RIS)} \mathbf{f}_{j'})^H\}] \right), j \in \mathcal{J}.$$

C17, C18, C19, C20, C21 **(P5)**

To relax constraint C20, a similar approach as in [3], where sequential rank one constraint relaxation (SROCR) technique has been used to relax the rank-one constraint of $\mathbf{P}$ iteratively. In the inner loop, the subproblem is solved iteratively by imposing the following constraint replacing C20.

$$\mathbf{C23}: \Upsilon(\mathbf{P}^{(t,r)})^H \mathbf{P} \Upsilon(\mathbf{P}^{(t,r)}) \geq \varrho^{(t,r)} \text{Tr}(\mathbf{P}), \quad (3.21)$$

where $\Upsilon(\mathbf{P}^{(t,r)})$ is the largest eigenvector at the outer iteration t and inner iteration r of the variable $\mathbf{P}$, $\varrho^{(t,r)} \leq 1$ a parameter that is being updated iteratively from 0 to 1 using equation 3.22.

$$\varrho^{(t,r)} = \min\left(\frac{\vartheta(\mathbf{P}^{(t,r)})}{\text{Tr}(\mathbf{P}^{(t,r)})} + \delta^{(t,r)}, 1\right), \quad (3.22)$$

where $\vartheta(\mathbf{P}^{(t,r)})$ refers to the largest eigenvalue of $\mathbf{P}^{(t,r)}$ and $\delta^{(t,r)}$ refers to the step

size. As a result, the newly formulated subproblem can be written as

$$\begin{aligned}
& \max_{\mathbf{P}, \bar{\nu}_{l,j}, \bar{\nu}_{e2}, \gamma^p, \gamma^n} - \sum_{j=1, \dots, J} [\text{Tr}(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j)^H \mathbf{P})] - \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P}) + \sum_{j=1}^{2J} \gamma^p_j + \sum_{j=1}^{2J} \gamma^n_j \\
& \text{s.t.} \\
& \bar{C}15, \bar{C}16, C17, C18, C19, C21, C22, C23. \tag{P6}
\end{aligned}$$

In which this subproblem is solved iteratively.

Thersholds Updating

In this subproblem, the thresholds related to the PUs and SU constraints are being updated given $\mathbf{F}^{(t)}$, and $\mathbf{p}^{(t)}$. Using the main constraints as in (P1) as follows

For the PUs thresholds, these thresholds are updated as in C24

$$\text{C24a : } \frac{|(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(\mathbf{P}, \text{RIS})}) \mathbf{f}_j|^2}{2 \left(\sum_{j' \in \mathcal{J} \setminus \{j\}} |(\mathbf{h}_{p,j}^H + \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(\mathbf{P}, \text{RIS})}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2 \right)} \geq \text{UP}_j^+ \quad j \in \mathcal{J}$$

$$\text{C24b : } \frac{|(\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(\mathbf{P}, \text{RIS})}) \mathbf{f}_j|^2}{2 \left(\sum_{j' \in \mathcal{J} \setminus \{j\}} |(\mathbf{h}_{p,j}^H - \mathbf{g}_{p,j}^H \mathbf{\Theta} \mathbf{H}_{(\mathbf{P}, \text{RIS})}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_{p,j}^H \mathbf{\Theta}\|^2 \right)} \geq \text{UP}_j^- \quad j \in \mathcal{J}$$

$$\text{C24c: } \text{UP}_j^+ + \text{UP}_j^- \geq \Psi_{s_j(\kappa)}, \quad j \in \mathcal{J}$$

where the thresholds related to the SU decoding each signal of the PUs one by one, will be updated as in constraint C25

$$\text{C25a: } \frac{|(\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{f}_j|^2}{2 \left(\sum_{j=j+1, \dots, J} |(\mathbf{h}_s^H + \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2 \right)} \geq \text{US}_j^+, \quad j \in \mathcal{J}$$

$$\text{C25b: } \frac{|(\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{f}_j|^2}{2 \left(\sum_{j=j+1, \dots, J} |(\mathbf{h}_s^H - \mathbf{g}_s^H \mathbf{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{f}_{j'}|^2 + \sigma_j^2 + \sigma_{\text{RIS}}^2 \|\mathbf{g}_s^H \mathbf{\Theta}\|^2 \right)} \geq \text{US}_j^-, \quad j \in \mathcal{J}$$

$$\text{C25c: } \text{US}_j^+ + \text{US}_j^- \geq \Psi_{s_j(\kappa)}, \quad j \in \mathcal{J}.$$

Therefore, the subproblem in this subsection will update the thresholds depending on the results of sub-problem (P3) and (P6) as follows

(P7): Thresholds updating

s.t.

C24, C25

The results of solving P7 will be used for the next iteration of sub-problem (P3) and (P6). The detailed solution is shown in algorithm 3 as well as in the flowchart 3.1.

3.3.2 Statistical CSI Error Model

In this subsection, the statistical CSI error model is going to be used to tackle the uncertainty of the channels related to the eavesdroppers. For this reason, the same problems P1, P6 and P7 will be solved with all constraints unrelated to the eavesdroppers will not be changed. Due to the fact that the estimation error usually follows a Gaussian distribution, which has no bound, the statistical CSI error model will be implied in this subsection where the constraints are related to

Algorithm 3 The AO Algorithm for Solving P1

```

1: Initialization: Iteration index  $t$ , convergence tolerance  $\Xi$ , reflection beam-
   forming vector  $\mathbf{p}^{(t)}$ ,  $\text{UP}^+(t)$ ,  $\text{UP}^-(t)$ ,  $\text{US}^+(t)$ , and  $\text{US}^-(t)$ .
2: repeat
3:   Solve P3 for  $\mathbf{F}_j^{(t)}$  for all  $j \in \mathcal{J}$ .
4:   if  $\text{rank}(\mathbf{F}_j^{(t)}) = 1$  for all  $j \in \mathcal{J}$  then
5:     Perform eigenvalue decomposition of  $\mathbf{F}_j^{(t)}$  to obtain  $\mathbf{f}_j^{(t)}$ .
6:     Go to step 17.
7:   else
8:     for  $i = 1, \dots, \text{maxIterations}$  do
9:       Generate a Gaussian random vector  $\mathbf{g}_i$  with zero mean and unit
       variance.
10:      Construct candidate solution  $\mathbf{f}_{j,i} = \mathbf{U}_1 \Sigma_1^{1/2} \mathbf{g}_i$  for all  $j \in \mathcal{J}$ .
11:      if (P3) is feasible with  $\mathbf{f}_{j,i}$  then
12:        Compute objective value with  $\mathbf{f}_{j,i}$ .
13:      end if
14:    end for
15:    return  $\mathbf{f}_j^{(t)} = \mathbf{f}_{j,i^*}$ , where  $i^* = \arg \min \text{objective}(i)$ .
16:  end if
17:  Initialize inner index  $r = 1$ .
18:  repeat
19:    With updated  $\mathbf{f}_j^{(t)}$ ,  $j \in \mathcal{J}$ , optimize reflection beamforming  $\mathbf{p}^{(t,r)}$ .
20:    Solve P6 to get  $\mathbf{p}^{(t,r+1)}$ .
21:    Update  $\varrho^{(t,r+1)}$  using equation 3.22.
22:  until Convergence is met
23:  Compute eigenvalue decomposition of  $\mathbf{P}^{(t,r+1)}$  as  $\mathbf{P}^{(t,r+1)} = \mathbf{U}_1 \Sigma_1 \mathbf{U}_1^H$ .
24:  return  $\mathbf{p}^{(t,r+1)} = \mathbf{p}_{i^*}$ .
25:  Update  $\text{UP}^+(t+1)$ ,  $\text{UP}^-(t+1)$ ,  $\text{US}^+(t+1)$ , and  $\text{US}^-(t+1)$  by solving
  (P7) with the given  $\mathbf{f}_j^{(t)}$ ,  $j \in \mathcal{J}$  and  $\mathbf{p}^{(t,r+1)}$ .
26:  Update  $t = t + 1$ .
27: until the difference between  $\text{Objective}(t+1)$  and  $\text{Objective}(t)$  is smaller than
   $\Xi$ .

```

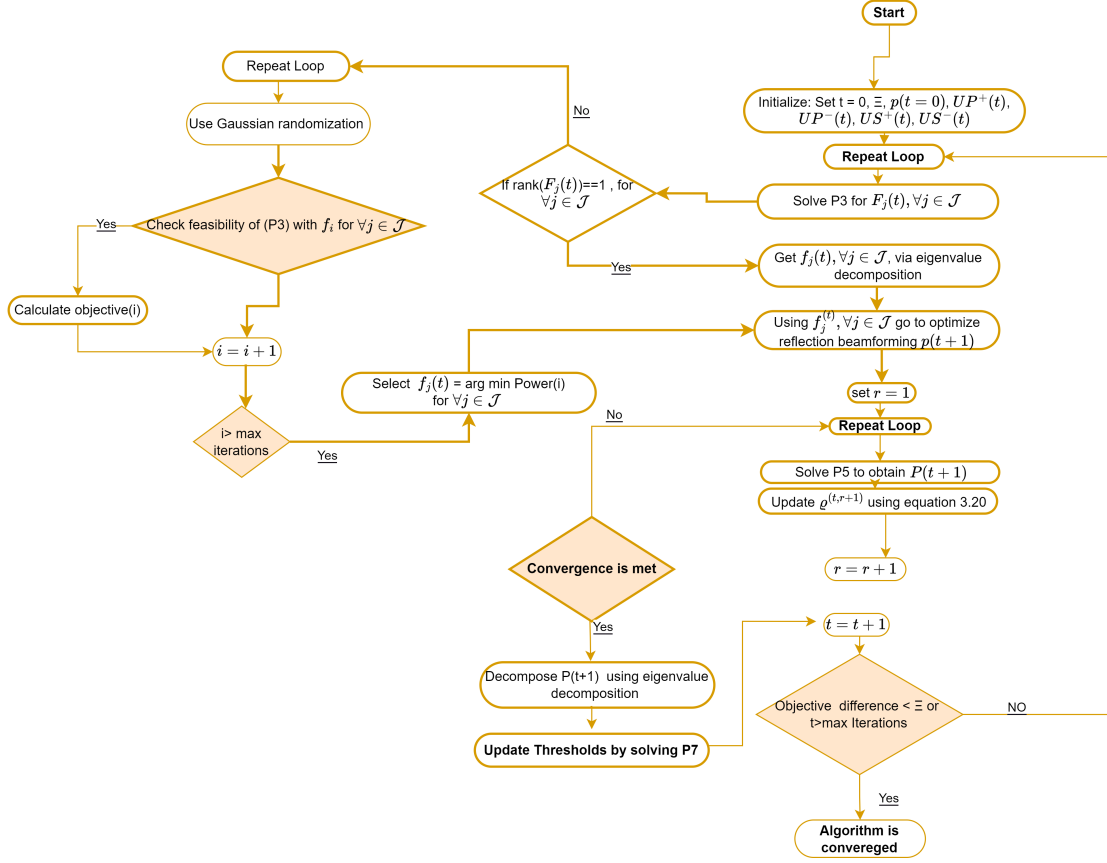


Figure 3.1: The flowchart of Algorithm 3.

the outage probabilities (i.e., $p_{e1,l}$ outage probability constant at the l^{th} EVs-I and p_{e2} is the outage probability at EVs-II). Therefore,

$$\text{C26: } \Pr \{ \Psi_{l,j} \leq \Psi_{\text{EVs-I}} \} \geq 1 - p_{e1,l} \quad (3.23)$$

$$\Delta \mathbf{h}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,l}), \quad l \in \mathcal{L}, j \in \mathcal{J}$$

C5 in P1 will also be written respectively as,

$$\text{C27: } \Pr \{ \Psi_{e2}^v \leq \Psi_{\text{EVs-II}} \} \geq 1 - p_{e2}$$

$$\Delta \mathbf{g}_{e2} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,e2}) \quad (3.24)$$

As a result, P1 will be reformulated as

$$\begin{aligned} \min_{\mathbf{F}, \boldsymbol{\Theta}} \quad & \sum_{j=1, \dots, J} \|\mathbf{f}_j\|^2 + N(P_{\text{SW}} + P_{\text{DC}}) + \sum_{j=1, \dots, J} [\|\boldsymbol{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2] + \sigma_{\text{RIS}}^2 \|\boldsymbol{\Theta}\|^2 - \sum_{j=1, \dots, J} \|\mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2 \\ \text{s.t.} \quad & \text{C1, C2, C3, C6, C26, C27} \quad (\mathbf{P8}) \end{aligned}$$

P8 is also a non-convex problem and a similar AO in Algorithm 2 will be used.

For tackling the CSI uncertainty error of the EVs channel, the Bernstein-Type Inequality as in Chapter 2, Section 2.4.2 has been used to reformulate C26, and C27. In the upcoming subsections, we introduce the solution of both $\mathbf{F}$ and $\boldsymbol{\Theta}$ optimization.

Transmit Beamforming Optimization

As in algorithm 2, we first perform optimization of the $\mathbf{F}_j, j \in \mathcal{J}$ given $\boldsymbol{\Theta}$, and the different thresholds (i.e., $UP_j^+, UP_j^-, US_j^+, US_j^-$), where in the first iteration they have been initialized as $\Psi_{s(\kappa)}/2$ for each one. All the constraints unrelated to the EVs will remain the same as in P3. Therefore, C28 can be reformulated as

$$\text{C26:} \quad \Pr \left\{ \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \left(\mathbf{h}_{e1,l}^H \mathbf{F}_j \mathbf{h}_{e1,l} + \mathbf{g}_{e1,l}^H \mathbf{B}_f^{l,j} \mathbf{g}_{e1,l} \right) \geq 0 \right\} \geq 1 - p_{e1,l},$$

$$\Delta \mathbf{h}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,l}), \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.25)$$

where

$$\mathbf{B}_f^{l,j} = \boldsymbol{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{F}_j \mathbf{H}_{(\text{P}, \text{RIS})}^H \boldsymbol{\Theta}^H - \Psi_{\text{EVs-I}} \sigma_{\text{RIS}}^2 \boldsymbol{\Theta} \boldsymbol{\Theta}^H$$

According to [3], this equation has no closed form which can be approximated as in *Lemma 2* in Chapter 2, Section 2.4.2, to make it computationally flexible and easy to handle by first assuming $\Sigma_{g,l} = \xi_{g,l}^2 I_N$ and $\Sigma_{h,l} = \xi_{h,l}^2 \mathbf{I}_M$ [29], [35]. Therefore, $\Delta \mathbf{h}_{e1,l} = \xi_{h,l} i_{h,l}$, $\Delta \mathbf{g}_{e1,l} = \xi_{g,l} i_{g,l}$, where $i_{h,l} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$ and $i_{g,l} \sim \mathcal{CN}(\mathbf{0}, I_N)$. As a result, equation (3.24) can be reformulated as

$$\Pr \{ \mathbf{i}_l^H \mathbf{W}_{l,j} \mathbf{i}_l + 2 \operatorname{Re} \{ \mathbf{b}_{e1,l}^H \mathbf{i}_l \} + b_{l,j} \geq 0 \} \geq 1 - p_{e1,l}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.25)$$

where

$$\mathbf{W}_{l,j} = \begin{bmatrix} -\xi_{g,l}^2 \mathbf{B}_f^{l,j} & \mathbf{0} \\ \mathbf{0} & -\xi_{h,l}^2 \mathbf{F}_j \end{bmatrix}, \quad \mathbf{b}_{l,j}^H = \begin{bmatrix} -\xi_{g,l} \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_f^{l,j} & -\xi_{h,l} \hat{\mathbf{h}}_{e1,l}^H \mathbf{F}_j \end{bmatrix},$$

$$b_{l,j} = \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \hat{\mathbf{h}}_{e1,l}^H \mathbf{F}_j \hat{\mathbf{h}}_{e1,l} - \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_f^{l,j} \hat{\mathbf{g}}_{e1,l}, \text{ and } \mathbf{i}_l = \begin{pmatrix} \mathbf{i}_{g,l} \\ \mathbf{i}_{h,l} \end{pmatrix}.$$

By using Lemma 2, we can approximate this constraint as follows while introducing slack variables $\mathbf{c} = [c_1, \dots, c_{L+J}]$ and $\mathbf{z} = [z_1, \dots, z_{L+J}]$,

$$\operatorname{Tr} \{ \mathbf{W}_{l,j} \} - \sqrt{2 \ln \left(\frac{1}{p_{e1,l}} \right)} z_{l,j} + \ln(p_{e1,l}) c_{l,j} + b_{l,j} \geq 0, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.26)$$

$$\sqrt{\| \mathbf{W}_{l,j} \|_F^2 + 2 \| \mathbf{b}_{e1,l} \|^2} \leq z_{l,j}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.27)$$

$$c_{l,j} \mathbf{I}_{M+N} + \mathbf{W}_{l,j} \succeq \mathbf{0}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.28)$$

To simplify (3.27), we can rewrite it as

$$\left\| \begin{array}{c} \xi_{g,l}^2 \text{vec}(\mathbf{B}_f^{l,j}) \\ \xi_{h,l}^2 \text{vec}(\mathbf{F}_j) \\ \sqrt{2} \xi_{g,l} \mathbf{B}_f^{l,j} \hat{\mathbf{g}}_{e1,l} \\ \sqrt{2} \xi_{h,l} \mathbf{F}_j \hat{\mathbf{h}}_{e1,l} \end{array} \right\| \leq z_{l,j}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.29)$$

In the same way, constraint C27 can be approximated by first considering

$$\Pr \{ \mathbf{i}_{e2}^H \mathbf{W}_{e2} \mathbf{i}_{e2} + 2\Re \{ \mathbf{b}_{e2}^H \mathbf{i}_{e2} \} + b_{e2} \geq 0 \} \geq 1 - p_{e2} \quad (3.30)$$

where $\mathbf{W}_{e2} = -\xi_{g,e2}^2 \mathbf{B}_f^{e2}$, $\mathbf{b}_{e2}^H = [-\xi_{g,e2} \hat{\mathbf{g}}_{e2}^H \mathbf{B}_f^{e2}]$, $b_{e2} = \sigma_{e2}^2 \frac{1}{K} \Psi_{Evs-II} - \hat{\mathbf{g}}_{e2}^H \mathbf{B}_f^{e2} \hat{\mathbf{g}}_{e2}$, $\mathbf{B}_f^{e2} = \sum_{j=1,\dots,J} [\mathbf{\Theta} \mathbf{H}_{(P,RIS)} \mathbf{F}_j \mathbf{H}_{(P,RIS)}^H \mathbf{\Theta}^H] - \frac{1}{K} \Psi_{Evs-II} \sigma_{RIS}^2 \mathbf{\Theta} \mathbf{\Theta}^H$ and $\mathbf{i}_{e2} = \mathbf{i}_{g,e2}$. Therefore, C27 can be approximated as

$$\text{Tr}\{\mathbf{W}_{e2}\} - \sqrt{2 \ln \left(\frac{1}{p_{e2}} \right)} z_{e2} + \ln(p_{e2}) c_{e2} + b_{e2} \geq 0 \quad (3.31)$$

$$\left\| \begin{array}{c} \xi_{g,e2}^2 \text{vec}(\mathbf{B}_f^{e2}) \\ \sqrt{2} \xi_{g,e2} \mathbf{B}_f^{e2} \hat{\mathbf{g}}_{e2} \end{array} \right\| \leq z_{e2} \quad (3.32)$$

$$c_{e2} \mathbf{I}_N + \mathbf{W}_{e2} \succeq \mathbf{0}, \quad (3.33)$$

Therefore, the subproblem will be similar to P2, where only the constraint of the

eavesdropper uncertainty will now be tackled using the statistical error model.

$$\min_{F, \mathbf{c}, \mathbf{z}, c_{e2}, z_{e2}} \sum_{j=1, \dots, J} [\text{Tr}(\mathbf{F}_j) + \text{Tr}((\mathbf{H}_{(P, \text{RIS})}^H \boldsymbol{\Theta}^H \boldsymbol{\Theta} \mathbf{H}_{(P, \text{RIS})}) \mathbf{F}_j) - \text{Tr}((\mathbf{H}_{(P, \text{RIS})}^H \mathbf{H}_{(P, \text{RIS})}) \mathbf{F}_j)]$$

s.t.

$$C8, C9, C10, C14, (3.26), (3.28), (3.29), (3.31), (3.32), (3.33) \quad (\mathbf{P9})$$

Reflection Beamforming Optimization

In this subproblem, a similar problem to **P5** will be solved, only constraints related to eavesdroppers will be approximated as in subsection A. With the given $\mathbf{F}^{(t)}$ by solving **P6**, we will focus on optimizing $\mathbf{P}^{(t+1)}$ under the statistical CSI error model.

C18 can be reformulated as

$$\Pr \left\{ \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \left(\mathbf{h}_{e1,l}^H \mathbf{F}_j \mathbf{h}_{e1,l} + \mathbf{g}_{e1,l}^H B_P^{l,j} \mathbf{g}_{e1,l} \right) \geq 0 \right\} \geq 1 - p_{e1,l} \quad (3.34)$$

$$\Delta \mathbf{h}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Sigma}_{h,l}), \quad \Delta \mathbf{g}_{e1,l} \sim \mathcal{CN}(\mathbf{0}, \boldsymbol{\Sigma}_{g,l}), \quad l \in \mathcal{L}, j \in \mathcal{J}$$

Where $\mathbf{B}_P^{l,j} = \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j) \mathbf{P} \text{diag}(\mathbf{H}_{(P, \text{RIS})} \mathbf{f}_j)^H - \sigma_{\text{RIS}}^2 \Psi_{\text{EVs-I}} \mathbf{P}$. Similarly, by using the same analysis in Lemma 2, this constraint can be approximated as

$$\text{Tr}\{\overline{\mathbf{W}}_{l,j}\} - \sqrt{2 \ln \left(\frac{1}{p_{e1,l}} \right)} \bar{z}_{l,j} + \ln(p_{e1,l}) \bar{c}_{l,j} + b_{l,j} \geq 0, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.35)$$

$$\left\| \begin{array}{c} \xi_{g,l}^2 \text{vec}(\mathbf{B}_P^{l,j}) \\ \xi_{h,l}^2 \text{vec}(\mathbf{F}_j) \\ \sqrt{2\xi_g} \mathbf{B}_P^{l,j} \hat{\mathbf{g}}_{e1,l} \\ \sqrt{2\xi_h} \mathbf{F}_j \hat{\mathbf{h}}_{e1,l} \end{array} \right\| \leq \bar{z}_{l,j}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.36)$$

$$\bar{c}_{l,j} \mathbf{I}_{M+N} + \bar{\mathbf{W}}_{l,j} \succeq \mathbf{0}, \quad l \in \mathcal{L}, j \in \mathcal{J} \quad (3.37)$$

$$\text{Where } \bar{\mathbf{W}}_{l,j} = \begin{bmatrix} -\xi_{g,l}^2 \mathbf{B}_P^{l,j} & \mathbf{0} \\ \mathbf{0} & -\xi_{h,l}^2 \mathbf{F}_j \end{bmatrix}, \quad \mathbf{b}_{e1,l}^H = \begin{bmatrix} -\xi_{g,l} \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_P^{l,j} & -\xi_{h,l} \hat{\mathbf{h}}_{e1,l}^H \mathbf{F}_j \end{bmatrix},$$

$$b_{l,j} = \sigma_{e1,l}^2 \Psi_{\text{EVs-I}} - \hat{\mathbf{h}}_{e1,l}^H \mathbf{F}_j \hat{\mathbf{h}}_{e1,l} - \hat{\mathbf{g}}_{e1,l}^H \mathbf{B}_P^l \hat{\mathbf{g}}_{e1,l}, \quad \mathbf{i}_l = \begin{pmatrix} \mathbf{i}_{g,l} \\ \mathbf{i}_{h,l} \end{pmatrix}.$$

In a similar way, constraint C19 can be reformulated as,

$$\Pr \left\{ \mathbf{i}_{e2}^H \bar{\mathbf{W}}_{e2} \mathbf{i}_{e2} + 2\Re \{ \mathbf{h}_{o,2}^H \mathbf{i}_{e2} \} + \mathbf{h}_{e2}^{\prime j} \geq 0 \right\} \geq 1 - p_{e2}, \quad (3.38)$$

$$\Delta \mathbf{g}_{e2} \sim \mathcal{CN}(\mathbf{0}, \Sigma_{g,o})$$

Where

$$\bar{\mathbf{W}}_{e2} = -\xi_{g,e2}^2 \mathbf{B}_P^{e2}, \mathbf{b}_{e2}^H = [-\xi_{g,e2} \hat{\mathbf{g}}_{e2}^H \mathbf{B}_P^{e2}], b_{e2} = \sigma_{e2}^2 \frac{1}{K} \Psi_{(EVs-II)} - \hat{\mathbf{g}}_{e2}^H \mathbf{B}_P^{e2} \hat{\mathbf{g}}_{e2}, \quad \mathbf{i}_{e2} = \mathbf{i}_{g,e2},$$

and $\mathbf{B}_P^{e2} = \sum_{j=1,\dots,J} [\text{diag}(\mathbf{H}_{(P,RIS)} \mathbf{f}) \mathbf{P} \text{diag}(\mathbf{H}_{(P,RIS)} \mathbf{f})^H] - \sigma_{\text{RIS}}^2 \frac{1}{K} \Psi_{(EVs-II)} \mathbf{P}$. This

gives the final form of constraint C19 as follows,

$$\text{Tr}(\bar{\mathbf{W}}_{e2}) - \sqrt{2 \ln \left(\frac{1}{p_{e2}} \right)} \bar{z}_{e2} + \ln(p_{e2}) \bar{c}_{e2} + b_{e2} \geq 0 \quad (3.39)$$

$$\left\| \begin{array}{c} \xi_{g,e2}^2 \text{vec}(\mathbf{B}_P^{e2}) \\ \sqrt{2} \xi_{g,e2} \mathbf{B}_P^{e2} \hat{\mathbf{g}}_{e2} \end{array} \right\| \leq \bar{z}_{e2} \quad (3.40)$$

$$\bar{c}_{e2} \mathbf{I}_N + \bar{\mathbf{W}}_{e2} \succeq \mathbf{0} \quad (3.41)$$

As a result, the new subproblem of optimizing the reflection beamforming under the statistical CSI error model can be reformulated as

$$\begin{aligned} \max_{\mathbf{P}, \bar{\mathbf{z}}_{l,j}, \bar{c}_{l,j}, \bar{z}_{e2}, \bar{c}_{e2}, \gamma^p, \gamma^n} & - \sum_{j=1, \dots, J} [\text{Tr}(\text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j) \text{diag}(\mathbf{H}_{(\mathbf{P}, \text{RIS})} \mathbf{f}_j)^H \mathbf{P})] - \sigma_{\text{RIS}}^2 \text{Tr}(\mathbf{P}) + \\ & \sum_{j=1}^{2J} \gamma_j^p + \sum_{j=1}^{2J} \gamma_j^n \end{aligned}$$

s.t.

$$\bar{C}15, \bar{C}16, C17, C21, C22, C23, (3.35), (3.36), (3.37), (3.39), (3.40), \text{ and } (3.41) \quad (\mathbf{P10})$$

Thersholds Updating

Due to the fact that, (P7) is only intended to update the thresholds related to the PUs and SU only, therefore, the same formulation of (P7) will be used in this subsection.

The same algorithm 3 will be used to solve problems (P9), (P10), and (P7) in this subsection.

3.3.3 Gradient Search with Randomization Method for Multi-User Case

In this section, we extend the gradient search with the randomization method to the multi-user case, where each user j has its own beamforming vector $\mathbf{f}_j$. This modified method is applied to evaluate the performance of the proposed algorithm for a system with M transmit antennas, N reflecting elements, and J users. The method serves as a benchmark to compare the suboptimal solution generated by our proposed algorithm.

The problem is formulated as:

$$\begin{aligned}
& \min_{\{\mathbf{f}_j\}, \boldsymbol{\Theta}} \quad \sum_{j=1}^J \|\mathbf{f}_j\|^2 + N(P_{\text{SW}} + P_{DC}) + \sum_{j=1}^J \|\boldsymbol{\Theta} \mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2 + \sigma_{\text{RIS}}^2 \|\boldsymbol{\Theta}\|^2 - \sum_{j=1}^J \|\mathbf{H}_{(\text{P}, \text{RIS})} \mathbf{f}_j\|^2 \\
& \text{s.t.} \\
& \text{C1: } \Psi_{p,j} \geq \Psi_{s(\kappa)}, \quad j \in \mathcal{J}, \\
& \text{C2: } \Psi_S^{(\kappa)} \geq \Psi_{s(\kappa)}, \\
& \text{C3: } \Psi_S^v \geq \Psi_v, \\
& \text{C6: } 0 \leq a_n \leq \rho, \quad 0 \leq \phi_n \leq 2\pi, \quad n \in \mathbf{N}. \quad (\text{P1})
\end{aligned}$$

Here, $\mathbf{f}_j$ is the beamforming vector for user j , $\boldsymbol{\Theta}$ is the diagonal RIS phase shift matrix, P_{SW} is the power consumption per RIS element, P_{DC} is the direct current power, $\mathbf{H}_{(\text{P}, \text{RIS})}$ represents the channel between the transmitter and the RIS, and σ_{RIS}^2 is the noise variance at the RIS.

The gradients of the objective function for the multi-user case are derived as

follows:

$$\nabla_{\mathbf{f}_j} \mathcal{L} = 2\mathbf{f}_j + 2\mathbf{H}_{(\text{P,RIS})}^H \boldsymbol{\Theta}^H \boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \mathbf{f}_j - 2\mathbf{H}_{(\text{P,RIS})}^H \mathbf{H}_{(\text{P,RIS})} \mathbf{f}_j, \quad (3.42)$$

$$\nabla_{\boldsymbol{\Theta}} \mathcal{L} = \sum_{j=1}^J 2\boldsymbol{\Theta} \mathbf{H}_{(\text{P,RIS})} \mathbf{f}_j \mathbf{f}_j^H \mathbf{H}_{(\text{P,RIS})}^H + 2\sigma_{\text{RIS}}^2 \boldsymbol{\Theta}. \quad (3.43)$$

To solve the optimization problem, the steps in Algorithm 4 are implemented. This approach ensures that the proposed algorithm produces a competitive sub-optimal solution, demonstrating its effectiveness in meeting the constraints and achieving good performance. Using gradient search with extensive randomization provides a robust benchmark for comparison.

To ensure a fair comparison, we evaluated the performance of our algorithm against Algorithm 2 by considering only the constraints C_1 , C_2 , C_3 , and C_6 across different values of Ψ_v . While Algorithm 2 demonstrates a good solution to the problem for small-scale systems, it is evident from Figure 2.4 that our proposed method consistently outperforms it. This is true even after running the Gradient Search method with 100,000 randomizations, despite the fact that Gradient Search does not guarantee an optimal solution.

3.4 Results and Discussion

In this section, the simulation results were conducted to evaluate the proposed algorithm where the passive RIS was considered a benchmark. Unless stated otherwise, the simulation parameters are listed in Table 3.1.

Figure 3.2 presents a comparison between the proposed Algorithm 3 and the Gradient Search optimization method detailed in Algorithm 4, evaluated after

Algorithm 4 Gradient Search Optimization with Randomizations for Multi-User Case

- 1: **Input:** System parameters $H, N, P_{\text{SW}}, P_{\text{DC}}, \sigma_{\text{RIS}}, \dots$, number of randomizations num_randomizations, step size step_size, tolerance tol, maximum iterations max_iter.
- 2: **Output:** Optimal beamforming vectors $\{f_{j,\text{opt}}\}, \forall j \in \mathcal{J}$, optimal RIS matrix Θ_{opt} , objective value f_{val} .
- 3: **Initialization:**
- 4: Set best_F = $\emptyset$, best_Theta = $\emptyset$, best_obj_val = ∞ .
- 5: **for** rand_iter = 1 to num_randomizations **do**
- 6: **Generate random initial values:**

$$f_{j,0} \sim \mathcal{CN}(0, I_M), \quad j = 1, \dots, J,$$

$$\Theta_0 = \text{diag}(\rho_n \cdot e^{j\theta_n}),$$

where ρ_n and θ_n are initial amplitudes and phases of the n^{th} RIS element.

- 7: Set $f_j = f_{j,0}, \forall j \in \mathcal{J}, \Theta = \Theta_0, \text{iter} = 0$.
- 8: **while** iter < max_iter **do**
- 9: Compute gradients:

$$\nabla_{f_j} = \text{GradientFunction}_{f_j}(f_j, \Theta), \quad \forall j,$$

$$\nabla_{\Theta} = \text{GradientFunction}_{\Theta}(\{f_j\}, \Theta).$$

- 10: Update variables:

$$f_j \leftarrow f_j - \text{step_size} \cdot \nabla_{f_j}, \quad \forall j,$$

$$\Theta \leftarrow \Theta - \text{step_size} \cdot \nabla_{\Theta}.$$

- 11: Evaluate objective function:

$$f_{\text{val}} = \text{ObjectiveFunction}(\{f_j\}, \Theta).$$

- 12: **if** $\|\nabla_{f_j}\| < \text{tol}$ **and** $\|\nabla_{\Theta}\| < \text{tol}$ **then**
 - 13: **Break.**
 - 14: **end if**
 - 15: Increment iter $\leftarrow \text{iter} + 1$.
 - 16: **end while**
 - 17: **if** $\{f_j\}$ and Θ satisfy constraints C_1, C_2, C_3, C_6 **and** $f_{\text{val}} < \text{best_obj_val}$ **then**
 - 18: Update best_F $\leftarrow \{f_j\}, \text{best_Theta} \leftarrow \Theta, \text{best_obj_val} \leftarrow f_{\text{val}}$.
 - 19: **end if**
 - 20: **end for**
 - 21: **Return:** $f_{j,\text{opt}} = \text{best_F}, \Theta_{\text{opt}} = \text{diag}(\text{best_Theta}), f_{\text{val}} = \text{best_obj_val}$.
-

Table 3.1: Simulation parameters 2.

Parameter	Value
PTx location (x, y)	$(0, 0)$ m
Number of PUs	$J = 2$
Number of EVs-I	$\mathcal{L} = 2$
RIS location (x, y)	$(18, 4)$ m
SU location (x, y)	$(20, 0)$ m
PU locations, randomly placed around (x, y)	$(80, 4)$ m
EVs type I locations, randomly placed around (x, y)	$(80, 2)$ m
EVs type II locations, randomly placed around (x, y)	$(20, 2)$ m
Carrier frequency f_c	800 MHz
The path-loss exponents for channels related to RIS	$\delta_{\text{PU, RIS}} = 2.4,$
$\delta_{\text{transmitter, receiver}}$	$\delta_{\text{RIS, EVs}} = 4,$
	$\delta_{\text{RIS, SU}} = 3,$
	$\delta_{\text{SU, PT}} = 2.4,$
	$\delta_{\text{PT, RIS}} = 2.4$
For those unrelated to RIS δ	$\delta = 4$
The Rician factor Γ	5
PTx antennas no. M	$M = 6$
RIS reflection elements no. N	$N = 16$
All additive noise power σ^2	-90 dBm
The maximum amplification of the active RIS ρ^2	10
Direct current biasing power at each RIS element P_{DC}	-5 dBm
Switch and control power of each RIS element P_{SW}	-10 dBm
SNR thresholds	$\Psi_v = 60$ dB, $\Psi_{s(\kappa)} = 24$ dB, $\Psi_{EVs_I} = 15$ dB, $\Psi_{EVs_{II}} = 15$ dB
The amount of uncertainties for Eavesdropper channels	$\xi_{g_1} = \xi_{h_1} =$ $\xi_{g_2} = \xi_{h_0} = 0.02$
The outage probability $p_{e1,l}$ and p_{e2}	$p_{e1,l}=0.05$ and $p_{e2}=0.05$

100,000 randomization trials. The figure highlights the relationship between total power consumption and the SNR required to decode v . Although Algorithm 4 produces a solution in small-scale systems, the results indicate that our proposed algorithm delivers superior performance, particularly in multi-user scenarios with interference. This advantage stems from the inherent limitations of search-based methods like Gradient Search when addressing constrained optimization problems. In this case, Gradient Search suffers from providing solutions outside the feasible

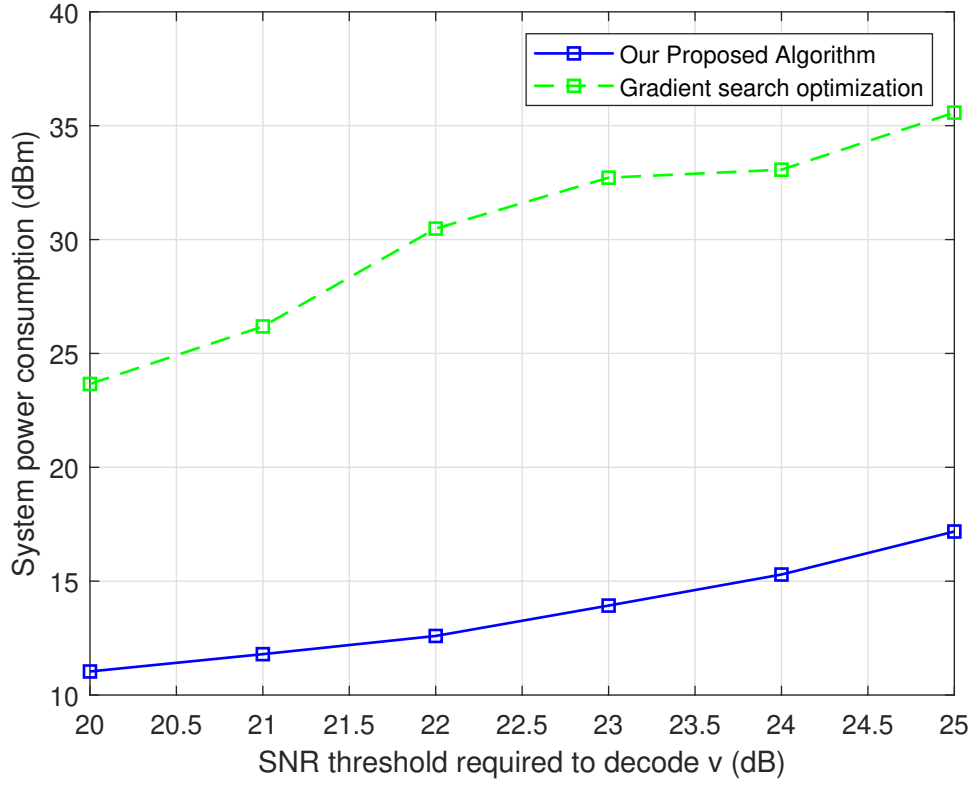


Figure 3.2: Comparison with the gradient search in Algorithm 4 with our proposed Algorithm.

set of constraints. Specifically, the need to project solutions onto the feasible constraint set often leads to suboptimal outcomes for Gradient Search. Even after 100,000 randomization trials, the Gradient Search method is unable to guarantee an optimal solution, further emphasizing the robustness of the proposed algorithm.

Figure 3.3 shows the convergence performance of the proposed Algorithm 3 for both passive and active RIS at $\Psi_v = 60dB$, and $N=16$. As we can notice from this figure, active RIS performs better by about 15dB over the passive RIS.

In Figure 3.4, we show the effect of increasing the uncertainty level ξ_{ho} on the total power consumption at $\Psi_v = 60$ dB. As shown in the figure, increasing this value will slightly increase the power consumption.

Figure 3.5 illustrates the impact of the number of RIS elements (N) on the total

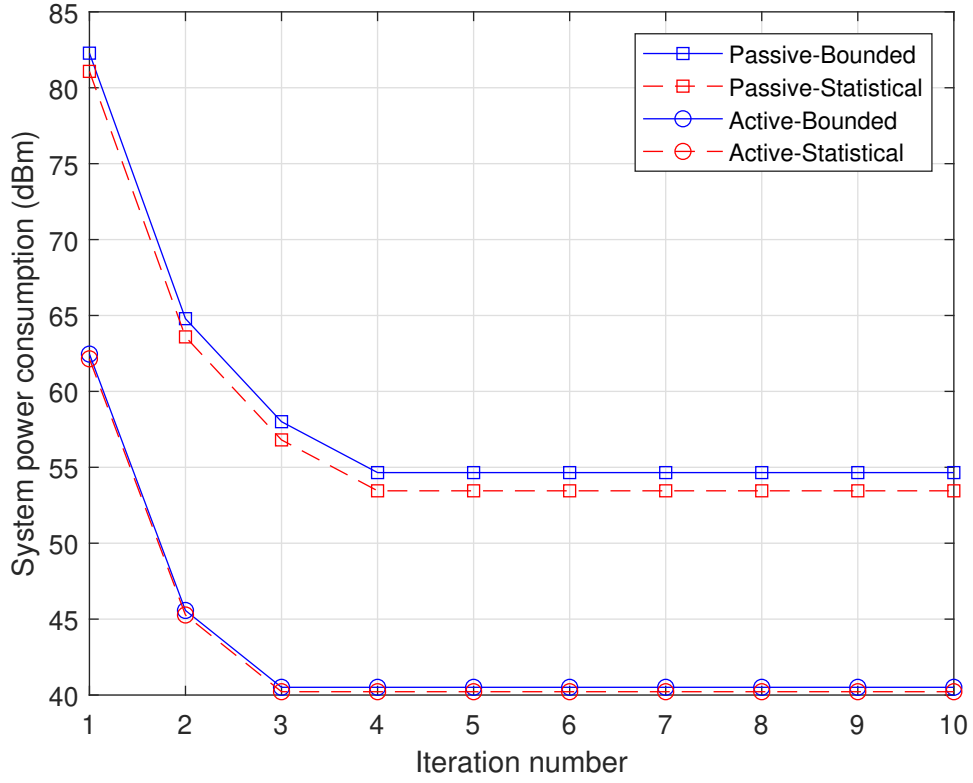


Figure 3.3: Convergence performance of Algorithm 3.

power consumption for two setups: multicast and multi-user beamforming, with an amplification factor of $\rho^2 = 15$. In both setups, increasing N initially reduces the total power consumption. However, the behavior diverges beyond certain points. For the multi-user beamforming case, the power consumption decreases up to $N^* = 20$, after which further increases in N lead to a rise in power consumption. This indicates that the multi-user configuration is highly sensitive to the choice of N . In contrast, the multicast setup exhibits a more stable performance. Even when the number of RIS elements exceeds $N^* = 30$, where power consumption starts to increase slightly, the rise is marginal compared to the multi-user case. This is due to the existence of interference in the multi-user beamforming case and the optimization under the worst-case scenario due to EVs.

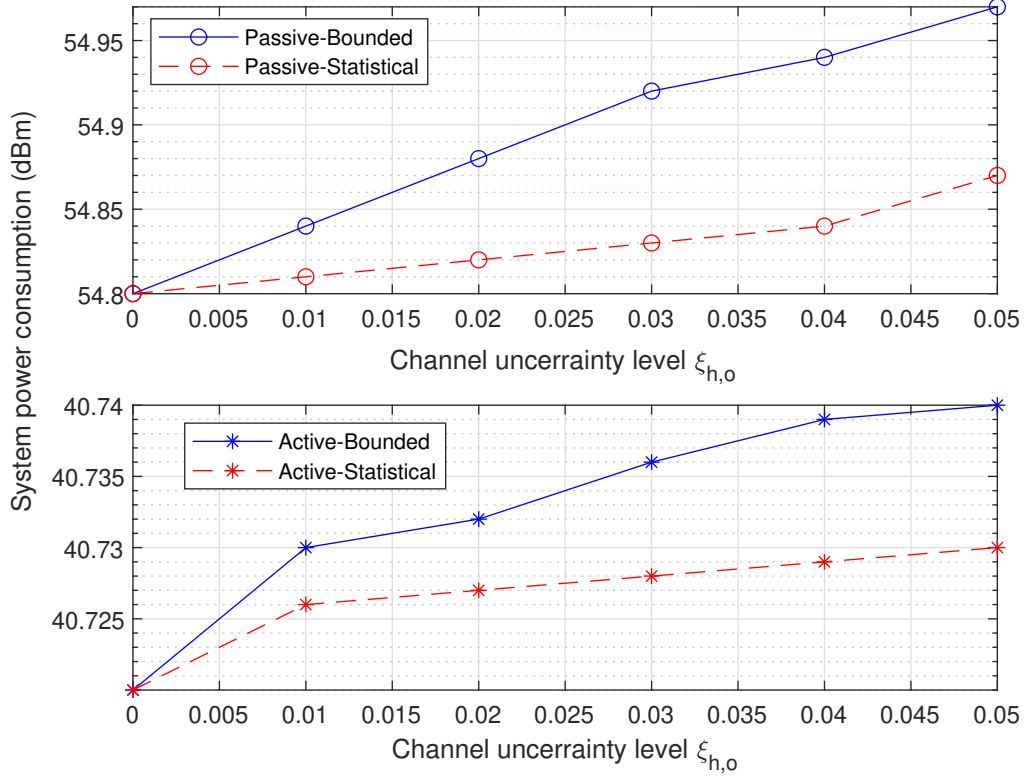


Figure 3.4: Total power consumption vs uncertainty level of the direct channel to EVs-II, ξ_{h_o} .

In figure 3.6, the effect of increasing the SNR requirement to decode the $s(\kappa)$ in dB, (at $\Psi_v = 45dB$) on the total power consumption for both active and passive RIS. As we can notice, by increasing the SNR by a small value, power consumption rises fast due to the effect of $\Psi_s(\kappa)$ threshold on different constraints that need to be met. Additionally, active RIS performs better than passive RIS, especially at higher SNR ranges.

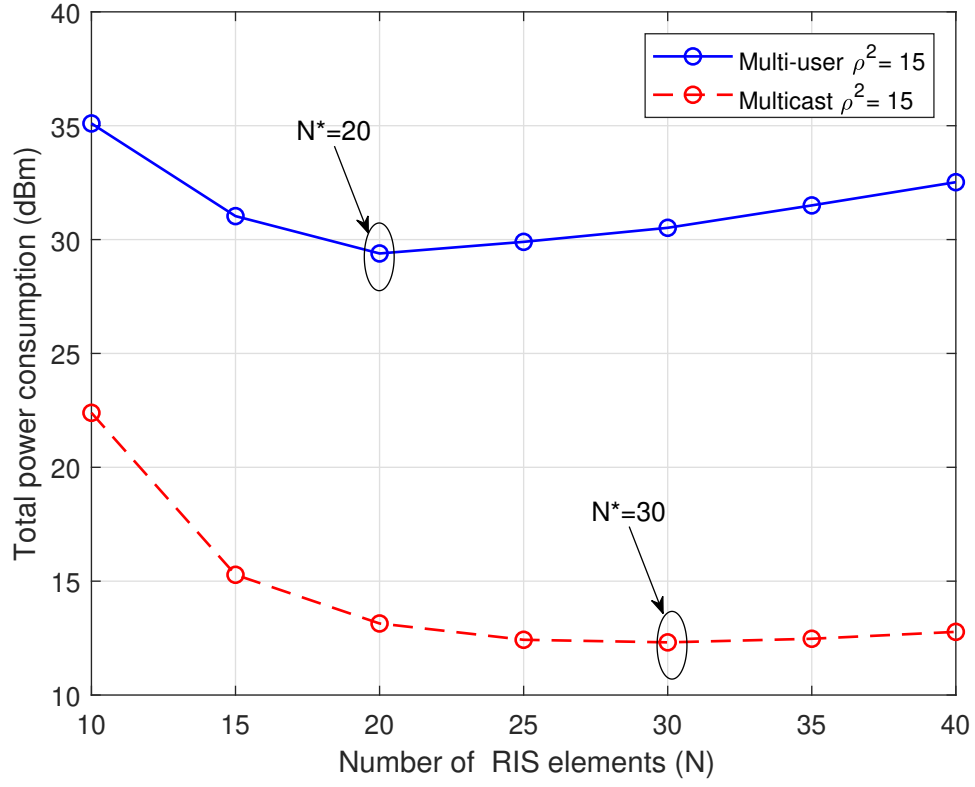


Figure 3.5: Total power consumption vs the number of RIS elements (N) for multicast and multi-user beamforming at active amplification factor $\rho^2 = 15$.

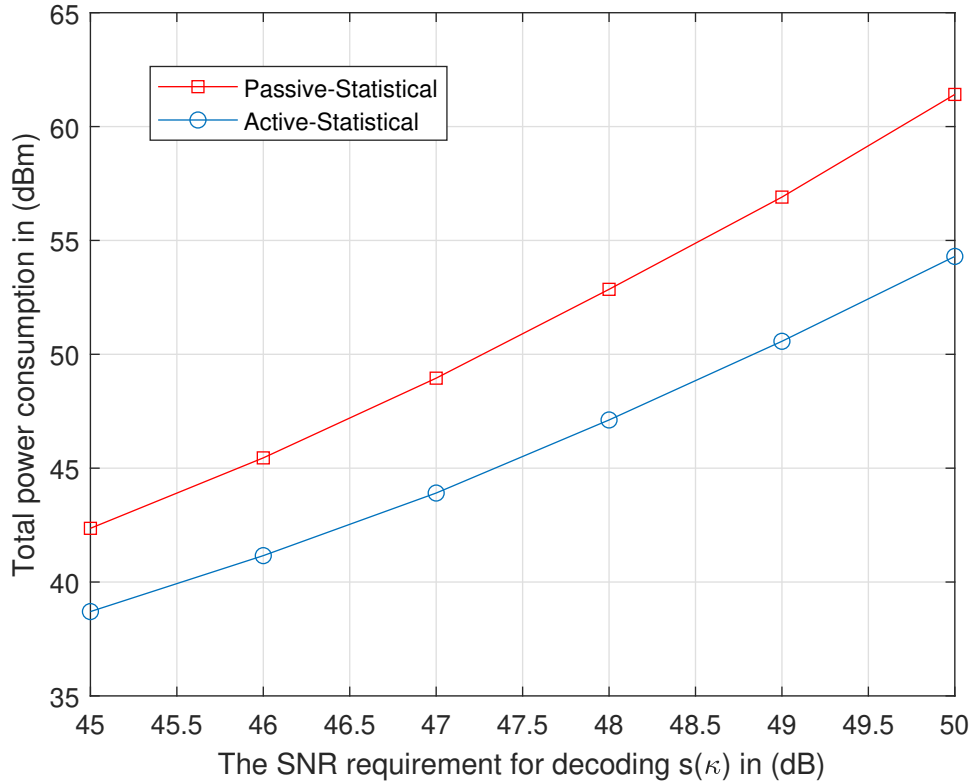


Figure 3.6: Power consumption vs the SNR for decoding $s(\kappa)$, $\Psi_s(\kappa)$.

Fig. 3.7 illustrates how the distance between the SU and the RIS impacts the overall power consumption. It is evident that as the SU moves farther away from the RIS, the power consumption increases to meet the QoS requirements of the SU.

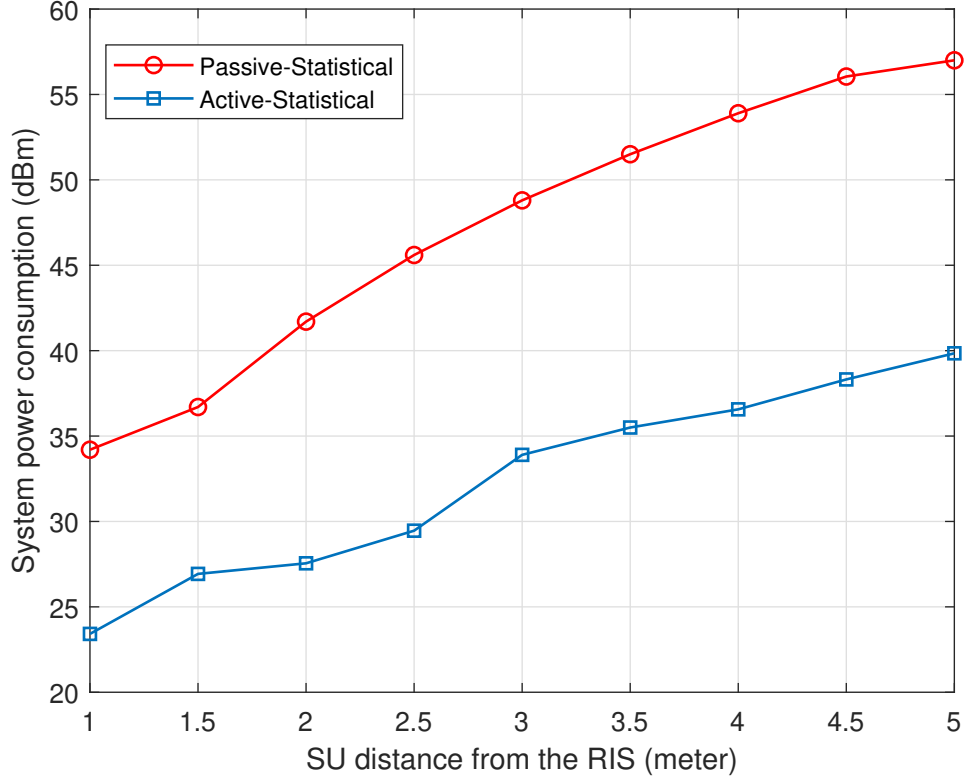


Figure 3.7: Power consumption vs the distance between the SU and RIS in meters.

Fig. 3.8 illustrates the effect of increasing the SNR requirement for decoding v as the SU. As the SNR increases, the power consumption increases where for low SNR, the difference between the active and passive RIS is around 7 dBm, while for higher SNR the difference become higher (i.e., around 17 dBm at SNR= 60dB).

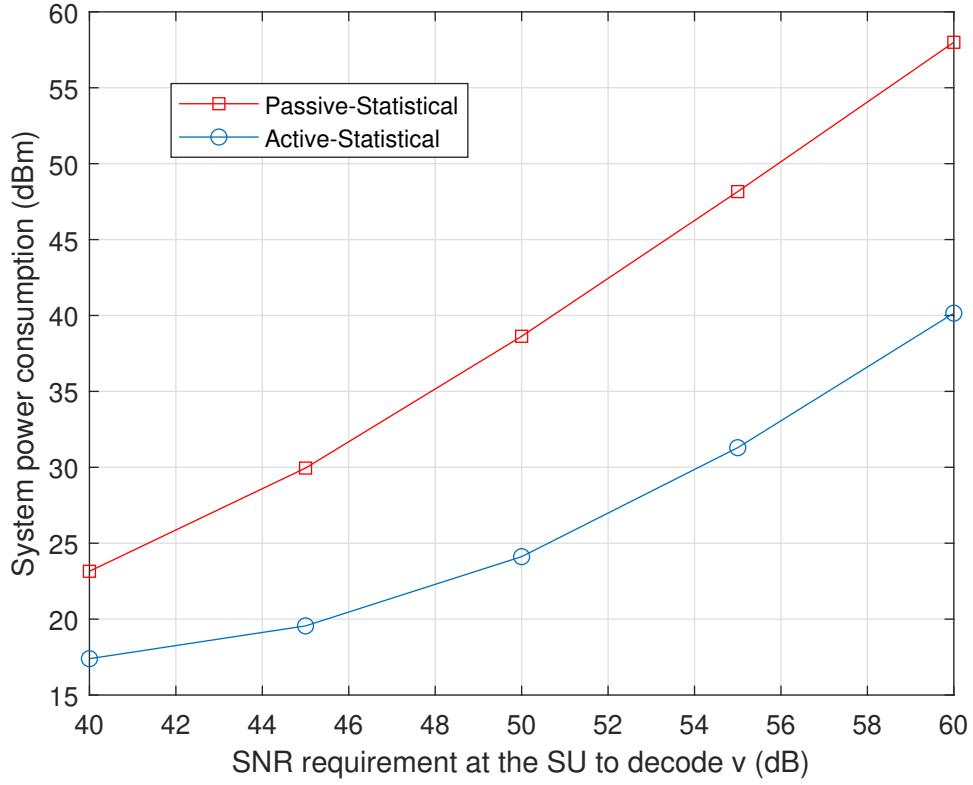


Figure 3.8: Power consumption vs SNR requirement at the SU to decode v , Ψ_v .

3.5 Conclusions

In this chapter, a multi-user beamforming at the PTx was introduced to the first problem of Chapter 2. Due to the fact now each user has distinct message transmitted from the PT, the interference between users will exist and create a significant complexity to the problem in Chapter 2. To deal with the new problem, we divided it into three subproblems and solved them iteratively as in Algorithm 3, where the third subproblem is meant to update the thresholds of the constraints related to the PUs and SU. On the other hand, we assumed that the eavesdroppers have the capabilities to eliminate the interference completely which leads to the use of

similar analysis of the uncertainties for both CSI error models with few differences. Three subproblems have been formulated and solved iteratively. Simulation results show significant improvement in the total power consumption using the proposed algorithm. The number of active RIS elements needs to be selected appropriately to balance between the amplification factor and power consumption, especially for the multi-user case.

CHAPTER 4

THESIS CONCLUSIONS AND FUTURE RESEARCH

4.1 Thesis Conclusions

In this thesis, joint beamforming optimization for an active RIS-assisted MIMO symbiotic radio (SR) system has been conducted to minimize total power consumption while satisfying Quality of Service (QoS) and Physical Layer Security (PLS) constraints for both primary users (PUs) and the secondary user (SU). The proposed system architecture consists of a primary transmitter (PT) equipped with M antennas, an active RIS with N reflection elements, J single-antenna PUs, L single-antenna eavesdroppers attempting to intercept messages transmitted from the PTx to the PUs, a type-2 eavesdropper intercepting information intended for the SU from the RIS, and a single-antenna SU. In Chapter 2, the problem was formulated as a single multicast transmit beamforming optimization at the PTx and reflection beamforming at the active RIS, where the PTx broadcasts the same message to all PUs. The objective was to minimize the total power consumption

at both the PTx and active RIS while fulfilling SNR requirements for all system components.

In Chapter 3, although the system architecture remained consistent, there were significant differences in the signal models, SNR expressions, and proposed optimization approach. Instead of optimizing a single beamforming vector at the PT, a multi-user transmit beamforming approach was used, introducing additional complexity due to user interference. To address this complexity, the original problem was divided into three subproblems: P1, which optimized the transmit beamforming vectors; P2, which optimized the reflection beamforming vector; and P3, which updated the thresholds for constraints related to the PUs and SU. A worst-case scenario was assumed for the eavesdroppers (EVs), where they could completely eliminate interference. Total power consumption is sensitive to the number of active RIS elements, and the maximum amplification factor of each element. As a result, they need to be selected carefully.

4.2 Future Research

There are several possible directions for future work to further develop and extend this thesis, some of which are outlined below:

- In the current system model, a potential extension could involve assuming that each eavesdropper is equipped with multiple antennas, thereby making the analysis more applicable to real-world scenarios.
- In the problem presented in Chapter 3, instead of assuming the worst-case scenario where the eavesdropper can eliminate interference, an alternative

approach could be to consider the presence of residual interference.

- Assessing the complexity of the proposed algorithms for larger numbers of users could be another meaningful extension.
- Exploring alternative algorithms to those presented in 1 and 3 to solve the same problem could be a worthwhile direction for further research.
- Shifting the focus to optimize different objectives, such as maximizing the secrecy rate or data rate, could also provide valuable insights.

REFERENCES

- [1] M. B. Janjua and H. Arslan, “A survey of symbiotic radio: methodologies, applications, and future directions,” *Sensors*, vol. 23, no. 5, p. 2511, 2023.
- [2] Y. L. Lee, D. Qin, L.-C. Wang, and G. H. Sim, “6g massive radio access networks: Key applications, requirements and challenges,” *IEEE Open Journal of Vehicular Technology*, vol. 2, pp. 54–66, 2020.
- [3] B. Lyu, C. Zhou, S. Gong, D. T. Hoang, and Y.-C. Liang, “Robust secure transmission for active ris enabled symbiotic radio multicast communications,” *IEEE Transactions on Wireless Communications*, vol. 22, no. 12, pp. 8766–8780, 2023.
- [4] Y.-C. Liang, Q. Zhang, E. G. Larsson, and G. Y. Li, “Symbiotic radio: Cognitive backscattering communications for future wireless networks,” *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 4, pp. 1242–1255, 2020.
- [5] G. Ghosh, P. Das, and S. Chatterjee, “Cognitive radio and dynamic spectrum access – a study,” *International Journal of Next-Generation Networks*, vol. 6, pp. 43–60, 03 2014.

- [6] D. K. P. Asiedu and J.-H. Yun, “Power resource optimization for backscatter-aided symbiotic full-duplex secondary transmission with hardware impairments in a cognitive radio framework,” *Sensors*, vol. 22, no. 1, 2022. [Online]. Available: <https://www.mdpi.com/1424-8220/22/1/375>
- [7] M. Ataeeshojai, R. C. Elliott, W. A. Krzymień, C. Tellambura, and I. Maljević, “Symbiotic backscatter communication underlying a cell-free massive mimo system,” *IEEE Internet of Things Journal*, vol. 10, no. 19, pp. 16 758–16 777, 2023.
- [8] R. Long, Y.-C. Liang, H. Guo, G. Yang, and R. Zhang, “Symbiotic radio: A new communication paradigm for passive internet of things,” *IEEE Internet of Things Journal*, vol. 7, no. 2, pp. 1350–1363, 2019.
- [9] Z. Zhang, L. Dai, X. Chen, C. Liu, F. Yang, R. Schober, and H. V. Poor, “Active ris vs. passive ris: Which will prevail in 6g?” *IEEE Transactions on Communications*, vol. 71, no. 3, pp. 1707–1725, 2023.
- [10] M. B. Janjua and H. Arslan, “A survey of symbiotic radio: Methodologies, applications, and future directions,” *Sensors*, vol. 23, no. 5, 2023. [Online]. Available: <https://www.mdpi.com/1424-8220/23/5/2511>
- [11] X. Zhou, L. Song, and Y. Zhang, *Physical layer security in wireless communications*. Crc Press, 2013.
- [12] N. Wang, P. Wang, A. Alipour-Fanid, L. Jiao, and K. Zeng, “Physical-layer security of 5g wireless networks for iot: Challenges and opportunities,” *IEEE internet of things journal*, vol. 6, no. 5, pp. 8169–8181, 2019.

- [13] O. Mehanna, N. D. Sidiropoulos, and G. B. Giannakis, “Multicast beamforming with antenna selection,” in *2012 IEEE 13th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2012, pp. 70–74.
- [14] A. Tarighat, M. Sadek, and A. Sayed, “A multi user beamforming scheme for downlink mimo channels based on maximizing signal-to-leakage ratios,” in *Proceedings. (ICASSP '05). IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.*, vol. 3, 2005, pp. iii/1129–iii/1132 Vol. 3.
- [15] 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, 2019.
- [16] K. Kishor and S. Hum, “An amplifying reconfigurable reflectarray antenna,” *IEEE Transactions on Antennas and Propagation - IEEE TRANS ANTENNAS PROPAGAT*, vol. 60, pp. 197–205, 01 2012.
- [17] Q. Zhang, Y.-C. Liang, and H. V. Poor, “Reconfigurable intelligent surface assisted mimo symbiotic radio networks,” *IEEE Transactions on Communications*, vol. 69, no. 7, pp. 4832–4846, 2021.
- [18] H. Guo, Y.-C. Liang, R. Long, and Q. Zhang, “Cooperative ambient backscatter system: A symbiotic radio paradigm for passive iot,” *IEEE Wireless Communications Letters*, vol. 8, no. 4, pp. 1191–1194, 2019.
- [19] J. Wan, Y. Guan, J. Song, Q. Song, and L. Guo, “Energy efficiency and spectral efficiency tradeoff in multi-bd symbiotic radio systems,” in *2023*

- IEEE/CIC International Conference on Communications in China (ICCC)*, 2023, pp. 1–6.
- [20] A. Al-Nahari, R. Jäntti, G. Zheng, D. Mishra, and M. Nie, “Ergodic secrecy rate analysis and optimal power allocation for symbiotic radio networks,” *IEEE Access*, vol. 11, pp. 82 327–82 337, 2023.
- [21] H. Chen, G. Yang, and Y.-C. Liang, “Joint active and passive beamforming for reconfigurable intelligent surface enhanced symbiotic radio system,” *IEEE Wireless Communications Letters*, vol. 10, no. 5, pp. 1056–1060, 2021.
- [22] M. Hua, L. Yang, Q. Wu, C. Pan, C. Li, and A. L. Swindlehurst, “Uav-assisted intelligent reflecting surface symbiotic radio system,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 9, pp. 5769–5785, 2021.
- [23] M. Hua, Q. Wu, L. Yang, R. Schober, and H. V. Poor, “A novel wireless communication paradigm for intelligent reflecting surface based symbiotic radio systems,” *IEEE Transactions on Signal Processing*, vol. 70, pp. 550–565, 2021.
- [24] L. Dong, H.-M. Wang, and J. Bai, “Active reconfigurable intelligent surface aided secure transmission,” *IEEE Transactions on Vehicular Technology*, vol. PP, pp. 1–1, 12 2021.
- [25] M. H. Khoshafa, T. M. N. Ngatched, M. H. Ahmed, and A. R. Ndjiongue, “Active reconfigurable intelligent surfaces-aided wireless communication system,” *IEEE Communications Letters*, vol. 25, no. 11, pp. 3699–3703, 2021.

- [26] K. Zhi, C. Pan, H. Ren, K. K. Chai, and M. ElKashlan, “Active ris versus passive ris: Which is superior with the same power budget?” *IEEE Communications Letters*, vol. 26, no. 5, pp. 1150–1154, 2022.
- [27] Z. Chu, W. Hao, P. Xiao, and J. Shi, “Intelligent reflecting surface aided multi-antenna secure transmission,” *IEEE Wireless Communications Letters*, vol. 9, no. 1, pp. 108–112, 2019.
- [28] L. Dong, H.-M. Wang, and J. Bai, “Active reconfigurable intelligent surface aided secure transmission,” *IEEE Transactions on Vehicular Technology*, vol. 71, no. 2, pp. 2181–2186, 2021.
- [29] S. Hong, C. Pan, H. Ren, K. Wang, K. K. Chai, and A. Nallanathan, “Robust transmission design for intelligent reflecting surface-aided secure communication systems with imperfect cascaded csi,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 4, pp. 2487–2501, 2020.
- [30] C. Wang, Z. Li, T.-X. Zheng, D. W. K. Ng, and N. Al-Dhahir, “Intelligent reflecting surface-aided secure broadcasting in millimeter wave symbiotic radio networks,” *IEEE Transactions on Vehicular Technology*, vol. 70, no. 10, pp. 11 050–11 055, 2021.
- [31] X. Xu, Y.-C. Liang, G. Yang, and L. Zhao, “Reconfigurable intelligent surface empowered symbiotic radio over broadcasting signals,” *IEEE Transactions on Communications*, vol. 69, no. 10, pp. 7003–7016, 2021.
- [32] B. Zheng, C. You, and R. Zhang, “Efficient channel estimation for double-irs aided multi-user mimo system,” *IEEE Transactions on Communications*, vol. 69, no. 6, pp. 3818–3832, 2021.

- [33] Z. Wang, L. Liu, and S. Cui, “Channel estimation for intelligent reflecting surface assisted multiuser communications: Framework, algorithms, and analysis,” *IEEE Transactions on Wireless Communications*, vol. 19, no. 10, pp. 6607–6620, 2020.
- [34] Z.-Q. He and X. Yuan, “Cascaded channel estimation for large intelligent metasurface assisted massive mimo,” *IEEE Wireless Communications Letters*, vol. 9, no. 2, pp. 210–214, 2019.
- [35] G. Zhou, C. Pan, H. Ren, K. Wang, and A. Nallanathan, “A framework of robust transmission design for irs-aided miso communications with imperfect cascaded channels,” *IEEE Transactions on Signal Processing*, vol. 68, pp. 5092–5106, 2020.
- [36] K.-Y. Wang, A. M.-C. So, T.-H. Chang, W.-K. Ma, and C.-Y. Chi, “Outage constrained robust transmit optimization for multiuser miso downlinks: Tractable approximations by conic optimization,” *IEEE Transactions on Signal Processing*, vol. 62, no. 21, pp. 5690–5705, 2014.
- [37] R. Long, Y.-C. Liang, Y. Pei, and E. G. Larsson, “Active reconfigurable intelligent surface-aided wireless communications,” *IEEE Transactions on Wireless Communications*, vol. 20, no. 8, pp. 4962–4975, 2021.

VITAE

- Name: Muneef Abdulwasa Razaz Mohammed
- Nationality: YEMENI
- Date of Birth: 05/05/1995
- Email: *mneefbasha@gmail.com*
- Permanent Address: 24th street, SANA'A, YEMEN

Education

- B.S. in Communications and Computer Engineering, Taiz University, Yemen in 2020
- M.Sc. in Electrical Engineering, King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia in 2024.

Publications

- Banafaa, M., Pepeoğlu, Ö., Shayea, I., Alhammadi, A., Shamsan, Z., Razaz, M. A., ... and Al-Sowayan, S. (2024). A comprehensive survey on 5G-and-beyond networks with UAVs: Applications, emerging technologies, regulatory aspects, research trends and challenges. IEEE Access.

- Razaz, Muneef A., et al. "VLC Channel estimation for indoor environment using LSTM." 2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA). IEEE, 2024.
- Shadad, R. Q., Razaz, M. A., Ali, G. S., Mhammed, A. A., Qaid, H. A., Abdulatef, M. (2022, October). Efficient and Reliable Management of 5G Network Slicing based on Deep Learning. In 2022 2nd International Conference on Emerging Smart Technologies and Applications (eSmarTA) (pp. 1-5). IEEE.
- Makarem, M. A., Algaolahi, A. Q., Alhajri, A. A., and Razaz, M. A. (2024, August). Enhancing load balancing and Fault Tolerance in Real-Time Applications Using SD-WAN. In 2024 4th International Conference on Emerging Smart Technologies and Applications (eSmarTA) (pp. 1-6). IEEE.
- Makarem, Mohammed A., and Muneef A. Razaz. "Real-time big data analysis systems resulting from the Internet of Things (IoT)." (2023).
- Makarem, Mohammed A., and Muneef A. Razaz. "Role of Big Data Analytics in the Internet of Things: A Comprehensive Survey." 2023 3rd International Conference on Emerging Smart Technologies and Applications (eSmarTA). IEEE, 2023.