



**JOINT PHASE SHIFT AND BEAMFORMING CHANNEL ESTIMATION
FOR RECONFIGURABLE INTELLIGENT SURFACE MULTIPLE-INPUT
MULTIPLE-OUTPUT SYSTEMS**

By

AL-KAMIL WALAA HUSSEIN ALI

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,
in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

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DEDICATION

I would like to dedicate this thesis to my father. May God have mercy on him and make him enter his spacious paradise. My support comes from my daughters, my supervisor, and the entire committee. Their guidance and relentless support have been a great inspiration in the realization of this research.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

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Chairman : Professor Ir. Ts. Nor Kamariah binti Noordin, PhD
Faculty : Engineering

Channel estimation plays a crucial role in optimizing signal quality within wireless communication systems. Reconfigurable Intelligent Surfaces improve signal propagation through passive elements due to their low cost and high energy efficiency. With the increasing number of mobile users, 5G faces challenges, making accurate CSI acquisition in RIS-MIMO systems essential yet challenging for three reasons. This thesis aims to enhance channel estimation accuracy and capacity across various simulation scenarios. Channel estimation in RIS-MIMO systems faces three main challenges. First, multipath propagation causes interference due to reflections, diffractions, and scattering. Second, the least square estimation at pilot positions produces low-resolution, noisy images, reducing system accuracy. Finally, signals reflecting off the RIS undergo phase shifts and amplitude changes, requiring more pilot signals and passive elements, leading to high training overhead. These challenges highlight the complexity of RIS-MIMO and the need for advanced solutions to maximize its potential. Using different symbol mapping techniques, this thesis first introduces the Least Square (LS) estimator for various multipath fading channels.

Performance was evaluated based on Bit Error Rate (BER), Throughput, and Mean Square Error (MSE). Results indicate that the proposed LS method outperforms the traditional LS in Rayleigh, Rician, and AWGN channels, especially for 64-QAM in downlink scenarios. Using a diamond pilot pattern, the proposed LS reduces BER at 20 dB by approximately 50% for AWGN, 40% for Rayleigh, and 33.33% for Rician compared to the traditional LS with a block pilot pattern. Second, we introduced the Super Resolution Image Restoration Channel Network (SRIR-ChNet) algorithm, which addresses the cascaded downlink RIS-MIMO channel estimation by framing it as an image super-resolution task to improve the accuracy of low-resolution estimates and noisy channel representations. The results indicate that SRIR-ChNet achieves MSE values between 10^{-4} and 10^{-3} , outperforming Generative Adversarial Networks for convolutional blind denoising networks (GAN-CBD) and CAE-ChannelNet. Additionally, SRIR-ChNet has a total time complexity of 0.86×10^{-2} s, which is lower than CAE-ChannelNet and GAN-CBD. Finally, we proposed the PSBA-H model for cascaded and separated channels and developed a system to manage the challenges associated with active and passive elements in the RIS. We analyze two scenarios: the estimation of the downlink cascaded MIMO channel from BS to UE via the RIS and the separate estimation of the BS-RIS and RIS-UE channels. The results show that the PSBA- $H_{T,K,R}$ method for the downlink cascaded channel achieves superior capacity performance, reaching 14.3 bits/Hz at 30 dB SNR with $K=32$ elements, outperforming DDL (11.2 bits/Hz) and DQN (11 bits/Hz). In separate downlink channels, PSBA- $H_{T,K}$ reaches approximately 19 bits/Hz with $K=64$ elements and 13 bits/Hz with $K=32$ at 30 dB SNR. Similarly, for separate uplink channels, the PSBA- $H_{K,R}$ method achieves nearly 18.5 bits/Hz at 30 dB SNR with $K=64$ elements and 12.3 bits/Hz with $K=32$. The results indicate that the proposed PSBA-H methods for the cascaded

channel take about 0.0075 seconds, while the separate channels range from 0.0092 to 0.0095 seconds. The PSBA-H model outperforms DDL and DQN in capacity and computational efficiency due to joint optimization of the phase shift and beamforming matrix toward accurate channel estimates in RIS-MIMO systems.

Keywords: Channel estimation, RIS, Beam-forming, Phase shift, Deep Learning.

SDG: GOAL. 7: Affordable and Clean Energy, GOAL. 11: Sustainable Cities and Communities, GOAL. 13: Climate Action.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**ANGGARAN SALURAN ANJAKAN FASA BERSAMA DAN
PEMBENTUKAN BAGI UNTUK SISTEM BERBELANDA PERMUKAAN
PINTAR YANG BOLEH DIKONFIRMASI SEMULA - PELBAGAI-
MASUKAN - OUTPUT**

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Anggaran saluran memainkan peranan penting dalam mengoptimumkan kualiti isyarat dalam sistem komunikasi tanpa wayar. Permukaan pintar yang boleh dikonfigurasi semula meningkatkan perambatan isyarat melalui unsur pasif kerana kos rendah dan kecekapan tenaga yang tinggi. Dengan peningkatan pengguna mudah alih, 5G menghadapi cabaran, menjadikan pemerolehan CSI yang tepat dalam sistem RIS-MIMO penting tetapi mencabar kerana tiga sebab. Tesis ini bertujuan untuk meningkatkan ketepatan anggaran saluran dan kapasiti merentas pelbagai simulasi. Anggaran saluran dalam sistem RIS-MIMO menghadapi tiga cabaran utama. Pertama, perambatan berbilang laluan menyebabkan gangguan akibat pantulan, pembelauan, dan serakan. Kedua, anggaran kuasa dua terkecil pada kedudukan perintis menghasilkan imej beresolusi rendah, bising, mengurangkan ketepatan sistem. Akhir sekali, isyarat yang mencerminkan RIS mengalami anjakan fasa dan perubahan amplitud, memerlukan lebih banyak isyarat perintis dan elemen pasif, yang membawa kepada overhead latihan yang tinggi. Cabaran ini menyerlahkan kerumitan RIS-MIMO

dan keperluan untuk penyelesaian lanjutan untuk memaksimumkan potensinya. Menggunakan teknik pemetaan simbol yang berbeza, tesis ini mula-mula memperkenalkan penganggar Kuasa Dua Terkecil (LS) untuk pelbagai saluran pudar berbilang laluan. Prestasi dinilai berdasarkan Kadar Ralat Bit (BER), Throughput dan Ralat Mean Square (MSE). Keputusan menunjukkan bahawa kaedah LS yang dicadangkan mengatasi LS tradisional dalam saluran Rayleigh, Rician dan AWGN, terutamanya untuk 64-QAM dalam senario pautan bawah. Menggunakan corak perintis berlian, LS yang dicadangkan mengurangkan BER pada 20 dB sebanyak lebih kurang 50% untuk AWGN, 40% untuk Rayleigh dan 33.33% untuk Rician berbanding LS tradisional dengan corak perintis blok. Kedua, kami mencadangkan algoritma Rangkaian Saluran Pemulihan Imej Resolusi Super (SRIR-ChNet) untuk mengganggu pautan ke bawah bertingkat RIS-MIMO dengan menganggapnya sebagai masalah resolusi super imej, bertujuan untuk meningkatkan ketepatan perwakilan saluran bising resolusi rendah. Keputusan menunjukkan bahawa SRIR-ChNet mencapai nilai MSE antara 10^{-4} dan 10^{-3} , mengatasi prestasi Generative Adversarial Networks untuk rangkaian denoising buta konvolusi (GAN-CBD) dan CAE-ChannelNet. Selain itu, SRIR-ChNet mempunyai jumlah kerumitan masa 0.86×10^{-2} s, yang lebih rendah daripada CAE-ChannelNet dan GAN-CBD. Akhir sekali, kami mencadangkan model PSBA-H untuk saluran bertingkat dan terpisah, yang direka khusus untuk menangani cabaran yang ditimbulkan oleh unsur aktif dan pasif dalam RIS. Dalam senario pertama, kami mengganggu saluran MIMO bertingkat bawah antara BS, RIS dan UE; dalam yang kedua, kami mengganggu saluran BS-RIS dan RIS-UE secara berasingan. Keputusan menunjukkan bahawa kaedah PSBA- $H_{T,K,R}$ untuk saluran bertingkat pautan bawah mencapai prestasi kapasiti yang unggul, mencapai 14.3 bit/Hz pada 30 dB SNR dengan elemen $K=32$, mengatasi

prestasi DDL (11.2 bit/Hz) dan DQN (11 bit/Hz). Dalam saluran pautan bawah yang berasingan, PSBA- $H_{T,K}$ mencapai lebih kurang 19 bit/Hz dengan elemen $K=64$ dan 13 bit/Hz dengan $K=32$ pada 30 dB SNR. Begitu juga, untuk saluran pautan atas yang berasingan, kaedah PSBA- $H_{K,R}$ mencapai hampir 18.5 bit/Hz pada 30 dB SNR dengan elemen $K=64$ dan 12.3 bit/Hz dengan $K=32$. Keputusan menunjukkan bahawa kaedah PSBA-H yang dicadangkan untuk saluran melata mengambil masa kira-kira 0.0075 saat, manakala saluran berasingan berjulat dari 0.0092 hingga 0.0095 saat. Model PSBA-H mengatasi prestasi DDL dan DQN dari segi kapasiti dan kecekapan pengiraan disebabkan pengoptimuman bersama anjakan fasa dan matriks pembentuk pancaran ke arah anggaran saluran yang tepat dalam sistem RIS-MIMO.

Kata kunci: Anggaran saluran, RIS, Pembentukan rasuk, Anjakan fasa, Pembelajaran Dalam.

SDG: MATLAMAT. 7: Tenaga Mampu Milik dan Bersih, MATLAMAT. 11: Bandar dan Komuniti Lestari, MATLAMAT. 13: Tindakan Iklim.

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LIST OF ABBREVIATIONS

N_s	Sensing Device
2D	Two-Dimensional
5G	Fifth Generation
6G	Sixth Generation
ADMM	Alternating Direction Method Of Multipliers
ANNs	Artificial Neural Networks
AWGN	Additive White Gaussian Noise
BA-CNN	Beamforming-Convolutional Neural Network
BER	Bit Error Rate
BF	Beamforming
Bi-LSTM	Bidirectional Long Short-Term Memory
BS	Base Station
BS-RIS	Base Station - Reconfigurable Intelligent Surface
C	Capacity
CAGAN	Conditional Generative Adversarial Network
CBDNet	Convolutional Blind Denoising Network
CCE	Cascaded Channel Estimation
CAE-ChannelNet	ConcreteAE Channel Network
CNN	Convolutional Neural Network
CR	Channel Reciprocity
CSI	Channel State Information
D	Destination
DL	Deep Learning
DnCNN	Denoising Convolutional Neural Network

DNNs	Deep Neural Networks
DReL	Deep Residual Learning
EM	Electromagnetic field
FDD	Frequency Division Multiplexing
FETs	Field-Effect Transistors
FFDNet	Fast and Flexible Denoising Convolutional Neural Network
FPGA	Field-Programmable Gate Array
GAN-CBD	Generative Adversarial Networks-Based Convolutional Blind Denoising
GANeT	Global Association Network
GHz	Gigahertz
HLA	Homogeneous Linear Array
HR	High Resolution
IoT	Internet of Things
IR	Image Restoration
ITU	International Telecommunication Union
KPIs	Key Performance Indicators
LLS	Link Level Simulator
LOS	Line-Of-Sight
LR	Low Resolution
LS	Least Square
LSTM	Long Short-Term Memory
M-EM-GAMP	Expectation-Maximization Gaussian-Mixture Approximate Message Passing
MEMS	Microelectronic Mechanical System
MIMO	Multiple-Input Multiple-Output
MISO	Multiple-Input Single-Output
ML	Maximum Likelihood

MMSE	Minimum Mean Square Error
mmWave	Millimeter Wave
MRDN	Multiple Residual Dense Networks
MSE	Mean Square Error
NLOS	NON-Line-Of-Sight
NMSE	Normalization Mean Square Error
NOMA	Non-Orthogonal Multiple Access
OFDM	Orthogonal Frequency Division Multiplexing
PAPR-FAC	Parallel Factor
PedA	PedestrianA
PIN	Positive-Intrinsic-Negative
PSBA-H	Phase Shift and Beamforming Channel Matrix
PS-CNN	Phase Shift-Convolutional Neural Network
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RBs	Resource Blocks
RELU	Reflective Linear Unit
RF	Radio Frequency
RIS	Reconfigurable Intelligent Surface
RNNs	Recurrent Neural Networks
Rx	Receiver
S	Source
SCE	Separate Channel Estimation
SISO	Single-Input Single-Output
SNR	Signal-to-Noise Ratio
SRCNN	Super Resolution Convolutional Neural Network
SRIR-ChNet	Super Resolution Image Restoration Channel Network

SVD-MMV-CS	Singular Value Decomposition- Model Composite Vector
Tbps	Terabit Per Second
TDD	Time-Division Multiplexing
THz	Terahertz
Tx	Transmitter
UE	User Equipment
UE-RIS	User Equipment - Reconfigurable Intelligent Surface
URLLC	Ultra-Reliable Low-Latency Communication
ZF	Zero Forcing

CHAPTER 1

INTRODUCTION

The research in wireless communication systems moves towards Reconfigurable intelligent surfaces (RIS). This new and revolutionary technology can significantly improve the performance of wireless communication networks by smartly reconfiguring the wireless propagation environment using massive low-cost passive reflecting elements integrated on a planar surface. Reconfigurable Intelligent Surfaces (RIS) and Multiple Input Multiple Output (MIMO) systems have emerged to address challenges in providing reliable, high-speed, and high-capacity wireless connections. RIS and MIMO have been extensively researched to exploit spatial freedom, improve signal quality, and amplify the system's capacity. However, effectively determining the communication channel's properties, known as channel estimation, remains a pivotal challenge, especially in complex settings such as RIS-MIMO systems. The fifth-generation (5G) network is constrained by its limited connectivity capacity and energy inefficiencies. As these limitations become more pronounced, there is growing interest in the development of sixth-generation (6G) technology. With 5G nearing its developmental ceiling, the escalating demands of the Internet of Things (IoT) necessitate more sophisticated communication systems that offer enhanced spectral efficiency and superior performance[1-6].

This chapter highlights the background of wireless communication systems and the problems existing in the RIS-MIMO system-based channel estimation. It states the main research objectives to be achieved and research questions to be answered,

followed by the scope and limitations of the study and the main contributions. Finally, this chapter outlines the thesis organization.

1.1 Background

As wireless communication continues evolving and permeating every corner of modern life, there's an ever-increasing demand for technologies that deliver faster speeds, more reliable connections, and broader bandwidths. Historically, we've transitioned from singular antenna systems to developing and deploying multiple-input and multiple-output (MIMO) systems. MIMO technology promises improved capacity without needing additional spectrum by utilizing multiple antennas at both the transmitter and receiver ends. More recently, the concept of Reconfigurable Intelligent Surfaces (RIS) has emerged, presenting an innovative way to shape the wireless environment. By smartly reflecting incoming signals, RIS offers a new dimension of flexibility to wireless communication, significantly enhancing the potential of MIMO systems. Reconfigurable Intelligent Surfaces (RIS) have recently garnered attention as a transformative technology in wireless communication. Essentially, RIS are programmable surfaces embedded with passive elements that can adaptively modify the behavior of incoming electromagnetic waves, enabling controlled reflection, refraction, or absorption [7]. Emerging as a promising solution to improve communication performance without significant power or spectrum increases, RIS technology offers the ability to reshape the wireless environment by controlling signal propagation. Specifically, RISs adjust the phase of incoming signals and optimize reflected waves to improve the received signal strength at the receiver [8]. Although the potential applications of RIS in enhancing communication quality, indoor wireless

systems, and even physical layer security are vast [9], challenges such as precise channel modeling and integration with current infrastructure remain to be addressed [10].

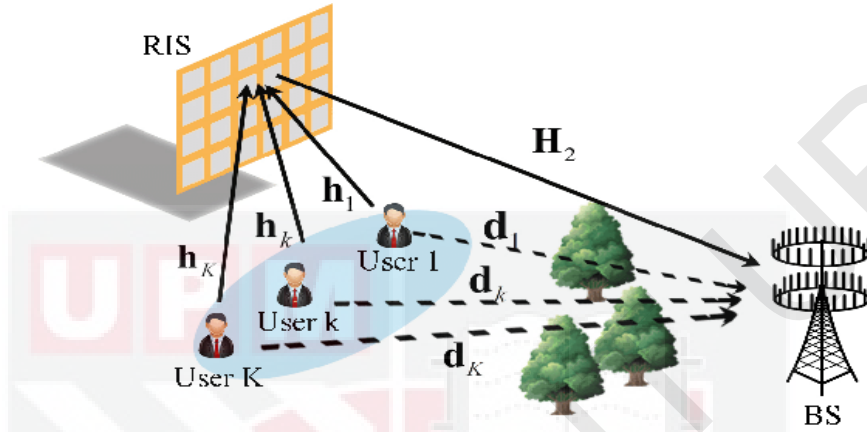


Figure 1.1: RIS-MIMO Systems [9]

In all communication systems, signals transfer data from the source to the destination. These signals traverse different media, which can be wired or wireless. Copper wires or fiber cables are two examples of wired media, while air is wireless. These media are also called channels. When a signal passes through the channel, it is distorted by the noise or other signals traversing that same medium. This means that when the signal is received at its destination, it could have errors. So, to remove the noise and distortion effects of the channel from the received signal, the channel's properties must be found. The process of figuring out channel characteristics is called Channel Estimation [10]. Channel estimation is the process by which the receiver attempts to estimate/predict the effect of the channel on the transmitted signal. Channel characteristics usually distort the received signal in a communication channel. The channel effect must be estimated at the receiver to recover the transmitted symbols. In the paradigm of Reconfigurable Intelligent Surfaces (RIS), the channel estimation

process is inherently more complex. This is due to the necessity of estimating multiple channels, i.e., the channel from the transmitter to the RIS and the channel from the RIS to the receiver. The channel from the transmitter/receiver to the RIS. This dual nature results in what's referred to as cascaded and separate channels.

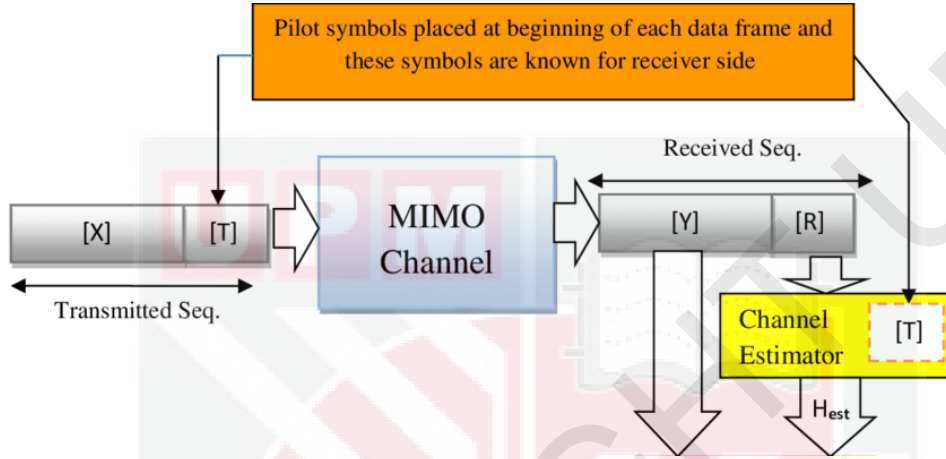


Figure 1.2: Non-blind channel estimation process[10]

Figure 1.2 illustrates the placement of the channel estimation downlink process. The X and T are the transmitted signal data symbols, and the pilot symbols matrix, T , is chosen to be an orthogonal matrix. The least-square algorithm detects the estimated channel matrix HLS from the Y and R received signal data sequence after passing through the MIMO channel and received pilot so that the loss function $\|Y - HLS X\|^2$ is minimized.

Cascaded channel estimation for RIS-MIMO communication systems is crucial for realizing the full potential of RIS in improving wireless communication. Channel estimation poses unique challenges because the RIS is typically a passive element without any transmit or receive capabilities. Traditional channel estimation techniques might not be directly applicable, and there's a need for innovative solutions [11].

Researchers have proposed various methods to estimate these cascaded channels. Some approaches involve evaluating the two channels separately and combining them for data transmission. Others suggest new pilot designs and estimation procedures consider RIS's unique reflective properties [12]. Given the rising interest in RIS and its potential impact on the future of wireless communication, the topic of cascaded channel estimation remains at the forefront of ongoing research. Developing efficient channel estimation techniques is vital for RIS to be integrated more widely into real-world communication systems [13]. Deep learning, a subset of machine learning rooted in artificial neural networks, excels at identifying intricate patterns and connections in data. Unlike traditional programming, deep learning models can learn these complexities without explicit instruction for every detail. Fueled by advancements in computing power and the abundance of large datasets, its popularity has surged recently. Drawing inspiration from the human brain's structure and function, these artificial neural networks, also called deep neural networks (DNNs), are designed to learn from vast amounts of data.

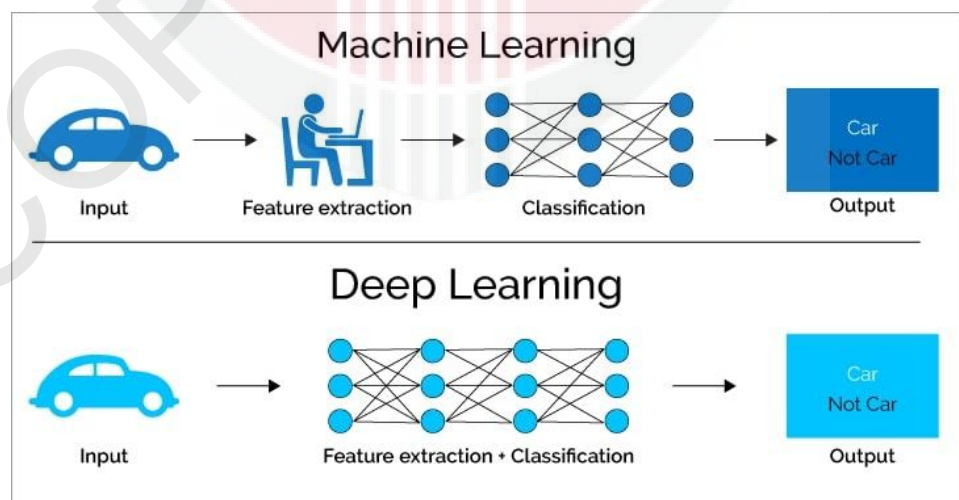


Figure 1.3: Comparing deep learning with machine learning [14]

Deep learning has become a significant and promising technology for communication systems in recent years. Specifically, its application to channel estimation, especially in systems utilizing Reconfigurable Intelligent Surfaces (RIS), has garnered substantial interest [15-16]. Reconfigurable Intelligent Surfaces (RIS) promise to reshape the future of wireless communication, providing flexible control over the propagation environment. However, a critical challenge for harnessing the full potential of RIS is channel estimation. Given the unique nature of RIS, traditional channel estimation methods might not suffice, especially considering the cascaded nature of the channels involved. Deep learning (DL) has demonstrated its proficiency in various wireless communication tasks in recent years. The application of DL to channel estimation in RIS is driven by its potential to model intricate and nonlinear systems, learning directly from data rather than relying on traditionally handcrafted algorithms [17]. Deep neural networks can be trained to predict the state of the cascaded channel based on pilot signals and observations, potentially offering more accurate and efficient estimation than traditional methods. Several architectures and techniques have been proposed, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to deal with the specific challenges posed by RIS-MIMO channel estimation [18]. The flexibility and adaptability of DL models make them particularly suited for this task, offering hope for more robust RIS-MIMO communication systems in the future [19]. Our proposed deep learning (DL) framework includes the complete set of necessary wireless communication functionalities: encoding, decoding, and channel estimation. In the field of signal processing, the transformation of signals into two-dimensional (2D) time-frequency images is a pivotal technique for analyzing the characteristics of signals across both time and frequency domains. This approach provides a comprehensive visualization

where each point in the image represents a time-frequency coordinate, with its intensity or color encoding information about the signal's magnitude or power at that point. By converting signals into 2D time-frequency images, we can effectively observe variations in the signal's frequency content over time, facilitating the detection of transient features and the analysis of non-stationary signals common in real-world scenarios. This method leverages techniques such as Short-Time Fourier Transform (STFT), Wavelet Transforms, or spectrograms to achieve a granular and dynamic representation of the signal. Notably, reference [20] pioneered treating the channel matrix as an image, focusing on its structural dimensions rather than the time-frequency properties of the communication link. Building on this, CAE-ChannelNet [21] was proposed as a deep learning channel estimation method. This approach views the channel grid with pilots as a low-resolution (LR) image and the target estimated channel as a high-resolution (HR) image, using a CNN to effectively perform super-resolution and estimate the channel.

1.2 Channel Estimation Challenges

Channel estimation in RIS-MIMO systems is significantly more challenging than in traditional MIMO systems equipped with active devices. This difficulty stems primarily from how Channel State Information (CSI) is acquired: while active systems allow straightforward acquisition using training sequences, the passive nature of the RIS (which lacks its own transmit/receive capabilities) limits estimation processes to rely on the active transceivers. Secondly, due to the high number of reflecting elements (REs) commonly found in RIS, significant training overhead is a major issue. Moreover, the interdependence of the transmitter-RIS and RIS-receiver channels, via the reflection coefficient matrix, makes separate CSI recovery difficult. In response,

researchers are exploring innovative channel estimation techniques for both cascaded and distinct channels, which include the transmitter-RIS and RIS-receiver links. In the following section, we examine a common scenario to highlight the importance of estimating these channels for optimizing joint active and passive beamforming in RIS-MIMO systems. Another issue is multipath fading, especially evident in RIS-MIMO systems. As signals traverse different paths due to environmental factors, they may converge at the receiver with varying phases and amplitudes, resulting in low estimation accuracy. Zhang et al.[22] highlighted the challenges in RIS-MIMO systems, noting that they can degrade image resolution in applications like radar imaging. The complexity of the reflection phase adds further difficulty, as each RIS element can introduce a unique phase shift, complicating channel estimation. Basar et al.[23] emphasized that this reflection phase directly affects the amplitude and phase of received signals, which is critical in scenarios requiring precise signal information. Deep learning-based channel estimation in RIS systems faces several challenges. The cascaded nature of RIS-MIMO systems complicates estimation beyond traditional MIMO settings. The numerous passive reflecting elements increase dimensionality, demanding deep learning models capable of processing large datasets, which may strain computational resources.

1.3 Problem Statement

Reconfigurable Intelligent Surface (RIS)-MIMO communication systems represent a promising technology for future wireless networks (5G and beyond), enhancing coverage, reliability, and efficiency. RISs actively shape the wireless environment, improving signal clarity and overall communication performance. However, integrating RIS into modern MIMO systems presents unique challenges, particularly

multipath fading. As signals reflect and scatter, they converge at the receiver with varying phases and amplitudes, leading to fading. Each passive RIS element can introduce distinct phase shifts, complicating channel estimation. Unintended phase shifts may cause destructive interference, adversely affecting signal integrity, which is critical for precise data interpretation and high-resolution imaging. These challenges highlight the complexities of RIS-MIMO systems and the need for advanced solutions to leverage this technology. Despite its potential, RIS faces issues such as multipath fading, phase complexity, pilot overhead, and inaccurate channel state information (CSI). Thus, this study focuses on addressing key problems in channel estimation for RIS-MIMO systems.

- i. Existing research has primarily focused on Line-of-Sight (LOS) conditions, resulting in limited attention to Non-Line-of-Sight (NLOS) scenarios. Consequently, current methods inadequately assess how multipath fading affects channel state information in both LOS and NLOS contexts, failing to specify which types of fading are effective in direct versus reflected paths. A comprehensive review of multipath fading is essential to enhance channel estimation in RIS-MIMO systems. This involves addressing the multiple paths that transmitted signals take to reach the receiver due to reflections, diffractions, and scattering, which can lead to constructive or destructive interference at the receiver.
- ii. The previous works are comparable to the MMSE and LS estimators as they serve as denoising models for these methods. However, they are not optimized in a fully end-to-end manner, This restricts their capability to learn complex, non-linear relationships between low-resolution and high-resolution images and to discern characteristic patterns of additive noise that would enhance the precision of channel estimation. To improve channel estimation precision within RIS-MIMO deployments, we reframe the acquisition of channel state information (CSI) as a problem of enhancing image resolution. We treat pilot-derived channel measurements as a coarse depiction, subsequently employing a sophisticated deep learning architecture, similar to a super-resolution convolutional neural network (SRCNN), to refine the estimation, to effectively extract and refine the intrinsic characteristics of the channel matrix. This approach enables both enhancement and denoising of the channel data, leading to improved estimation accuracy.

- iii. Reconfigurable Intelligent Surfaces (RIS) offer promising solutions for improving wireless communication systems by intelligently manipulating signals through programmable reflecting elements. However, when the transmitter sends a signal, and when the incident signal arrives at the fully passive RIS elements, the signal will reflect and then suffer from a change in phase shift and amplitude before arriving at the receiver. RIS elements are passive and must be intelligently controlled to optimize the phase of the reflected signals. Achieving optimal phase control can be complex and requires complicated algorithms. In a RIS-MIMO communication system, the channel coefficient exhibits exponential growth as the number of RIS elements increases, consequently causing a considerable rise in pilot overhead. Prior research has predominantly focused on formulating channel estimation algorithms for cascaded channels, leading to enhanced estimation accuracy. However, the issue of high training pilot overhead has often been overlooked in these discussions. Estimating the entire cascaded channel (BS-RIS-UE) with numerous passive elements K at the RIS significantly increases the training pilot overhead at the receiver. This is particularly challenging for the RIS-UE link, as it requires estimation on a short timescale due to user mobility.

1.4 Research Objectives

Accurate channel state information acquisition is significant for complex signal processing for the RIS-MIMO communication system. Due to the large number of antennas, the number of RF links is relatively small, and the low-dimensional compelling observations can be used to estimate the high-dimensional channel coefficients. This research investigates the channel estimation problems in the downlink cascaded channel and the uplink/downlink separate channel in RIS-MIMO systems by focusing on achieving higher data rates and high estimation accuracy. Effective and efficient channel estimation solutions are designed to achieve the desired performance. In addition, the thesis has the following main objectives:

- i. To model the channel time-frequency response by generating a new dataset with 5G specifications as a 2D image using the PedA model.
- ii. To propose a deep learning algorithm, SRIR-ChNet, to optimize the signal quality and channel estimation accuracy due to multipath fading of the transmitted signal in a cascaded channel RIS-MIMO downlink system.

- iii. To design and implement a new CNN approach for 2D image PSBA-H to study a two-stage channel estimation method for the cascaded and separate RIS-MIMO uplink/downlink communication system.
- iv. To evaluate the performance of all proposed channel estimation methods in the RIS-MIMO system using a set of performance metrics such as normalized mean square error and time complexity.

1.5 Research Questions

The following research questions have been outlined to be answered throughout this thesis:

- i. How does the dynamic nature of fast-fading channels influence the accuracy of channel state information (CSI) updates in reconfigurable intelligent surface-multiple input, multiple outputs (RIS-MIMO) systems transmitting data as images?
- ii. How can deep learning techniques be effectively employed for the simultaneous optimization of phase-shift and beamforming in the RIS-MIMO system based on cascaded and separate channel estimation?
- iii. How does the active control of phase shift by reconfigurable intelligent surface (RIS) elements contribute to optimizing signal reflection in RIS-MIMO systems, and how does this optimization influence the accuracy of channel estimation in the presence of fast-fading channels?

1.6 Research Motivation

Reconfigurable Intelligent Surfaces (RIS) have emerged as a key technology in wireless communications, enhancing signal coverage, boosting system capacity, and optimizing overall network performance. Due to their adaptable nature, reduced complexity, and power efficiency, RIS technology holds significant promise for the development of next-generation wireless systems, including 5G and beyond. In RIS-MIMO systems, accurate channel estimation is crucial for adapting to dynamic signal

variations. Fast fading, which causes rapid variations in signal strength and phase, necessitates continuous channel state information (CSI) updates for effective system operation. Image-based channel modeling emphasizes the importance of producing high-quality, noise-free representations to determine the channel state. It's vital to actively adjust phase shifts via RIS elements to optimize signal reflection to maintain reliable communication, especially when faced with fast-fading scenarios. This adaptability enables the system to respond dynamically. In short, the underlying motivation is to achieve responsiveness to evolving channel conditions, improving image data quality, and fine-tuning phase shift control to optimize signal transmission in RIS-MIMO systems.

1.7 Research Contributions

The main contributions of this thesis are summarized as follows:

- i. As a first contribution, we modeled the channel time-frequency response by generating a new dataset aligned with 5G specifications, represented as 2D images using the PedA model and MATLAB simulator. This effort resulted in 40,000 frames, each containing four 2D images depicting time-frequency responses across various channel models, including AWGN, Rayleigh, and Rician channels with 64-QAM modulation techniques. The PedA model aims to generate noisy channels through the least square channel estimation method, utilizing a diamond pilot pattern design for downlink transmission. Additionally, we explored the performance of RIS-MIMO downlink systems without channel estimation, analyzing various fast-fading channel models. The effectiveness of the least square (LS) channel estimation method was evaluated by comparing metrics such as bit error rate (BER), throughput, and mean square error (MSE) for 64-QAM modulation schemes across AWGN, Rayleigh, and Rician channels. This study provides a comprehensive review of multipath models for AWGN, Rayleigh, and Rician channels.
- ii. As a second contribution, we focus on the challenge of channel estimation in RIS-MIMO communication systems by formulating it as an image super-resolution (SR) problem. This approach treats the channel response at pilot positions as a low-resolution image, while the estimated channel response

represents the proposed high-resolution image. We developed deep convolutional neural network algorithms based on this formulation to enhance RIS-MIMO channel estimation. Specifically, our proposed framework, SRIR-ChNet, combines the Super-Resolution Convolutional Neural Network (SRCNN) and the Image Restoration Convolutional Neural Network (IRCNN) to reconstruct the channel matrix from pilot-derived channel estimates, thereby enhancing both interpolation and denoising. SRIR-ChNet significantly enhances channel estimation accuracy, reducing mean square error (MSE) compared to traditional methods. This deep learning-driven approach effectively optimizes channel estimation performance.

- iii. As a third contribution, we present a new method for channel estimation in RIS-MIMO systems, leveraging deep learning architectures specifically designed to handle the complexities of both active and passive RIS elements. Our study examines a two-step channel estimation process aimed at improving the performance of RIS-MIMO communication systems. In the first stage, we estimate the cascaded MIMO channel between the base station (BS), RIS, and user equipment (UE). In the second stage, we focus on estimating the base station to reconfigurable intelligent surfaces (BS-RIS) and reconfigurable intelligent surfaces to user equipment (RIS-UE) channels separately. We proposed two efficient deep neural networks, referred to as Net 1, phase shift Convolutional Neural Network (PS-CNN), and Net 2, beamforming Convolutional Neural Network (BA-CNN). Initially, the Net 1 addresses phase reflection complexities by determining optimal phase shifts and configuring the RIS phase shift matrix during training. Following training, a brute-force search algorithm is applied. Subsequently, the optimal beamforming vectors are computed using Singular Value Decomposition (SVD), which calculates the angles of departure (AoD) and angles of arrival (AoA) before the training of Net 2. This process enhances signal power and signal-to-noise ratio (SNR) at the receiver. The second network achieves joint beamforming and phase shift optimization to maximize channel capacity between the source (S) and destination (D).

1.8 Scope and Limitations of the Research

Figure 1.4 illustrates the flow of our research. The red squares indicate the path taken in this thesis to achieve our goals and objectives, while the black squares represent the specific objectives. The white boxes denote areas of research that fall outside the scope of this work. The figure highlights the key practical issues associated with RIS-MIMO systems. In this research, for dataset generation, we have used a widely used 5G simulator developed by the University of Vienna, Vienna 5G Link Level Simulator

[24], the primary software tools employed are MATLAB 2023a and Anaconda Spyder. MATLAB serves as a powerful environment for numerical computing and algorithm development, particularly useful for simulating and analyzing signal processing algorithms in RIS-MIMO systems. Keras and Tensorflow, using a GPU backend, are used for the implementation of our proposed scheme. Anaconda Spyder is utilized for training deep learning models, providing an integrated development environment that supports Python programming. This combination allows for efficient data manipulation, model training, and evaluation. Additionally, the experiments leverage an NVIDIA GPU, which enhances computational performance, particularly for deep learning tasks. The GPU accelerates the training of Convolutional Neural Networks (CNNs) by enabling faster processing of large datasets and complex models. All methods run on a desktop computer with an i9-12900H 3.30 GHz central processing unit (CPU) and an Nvidia GeForce RTX 3070Ti GPU. This thesis faces several limitations in channel estimation for RIS-MIMO systems. Both cascaded and separate channel estimation methods have their respective limitations that can hinder their effectiveness in RIS-MIMO systems: First, it does not fully explore the use of double/multi-RIS systems, which, while offering improved channel estimation, introduce increased complexity, interference management challenges, and higher energy consumption. Second, the study focuses on either separate or cascaded non-line of sight channel estimation, without investigating a hybrid approach that could dynamically switch between these methods for better performance. Third, the research does not address RIS in higher frequency bands (e.g., THz), which are crucial for 6G networks but face significant challenges in channel state information (CSI) acquisition due to RIS's passive nature. Finally, this work is limited to static or low-mobility scenarios and does not consider high-mobility environments, where rapidly changing conditions can affect the stability of RIS performance. These limitations highlight areas for future exploration.

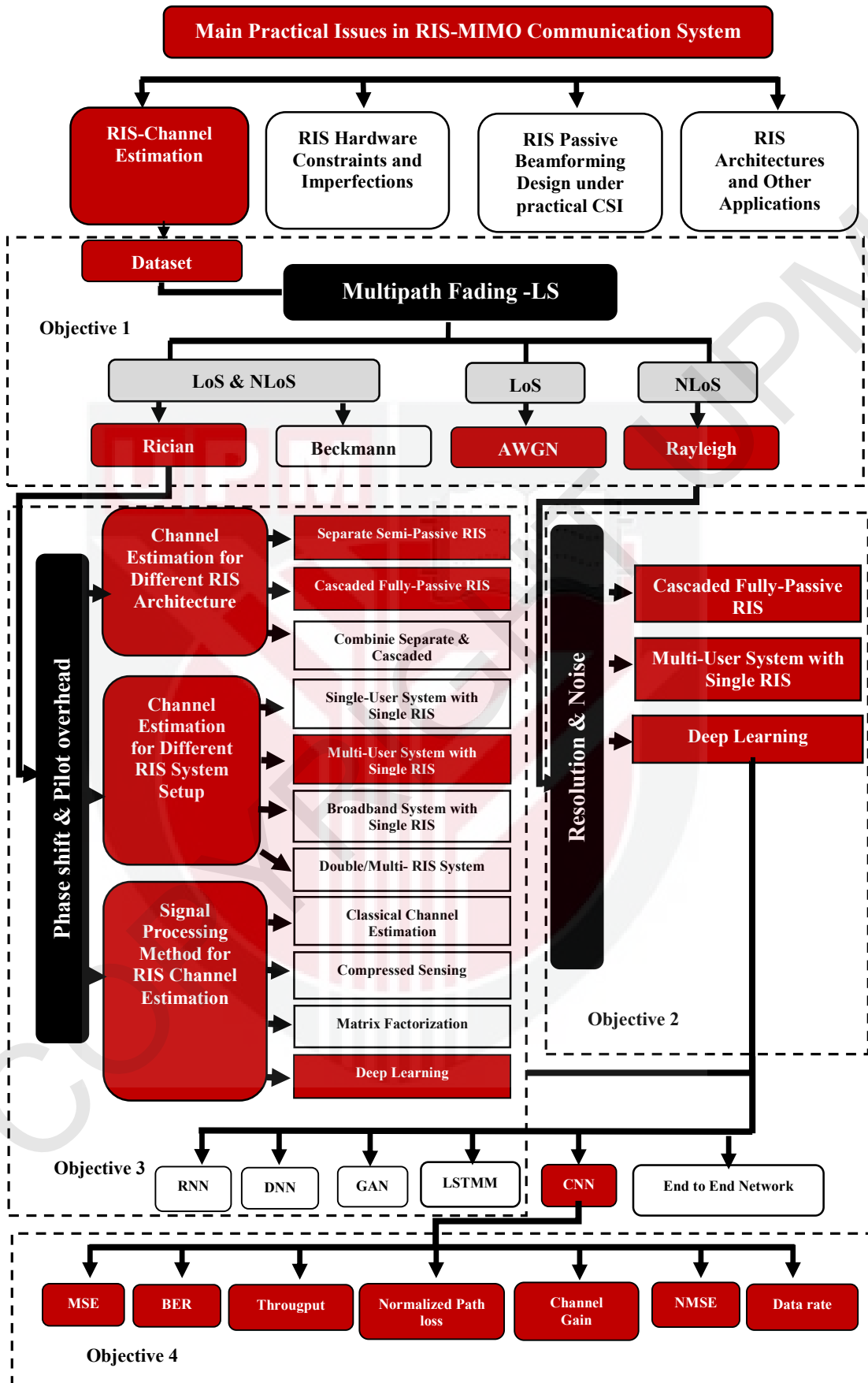


Figure 1.4: Study Module

1.9 Thesis Organization

With the development of high-speed and low-frequency communication, the academic community will pay more and more attention to the bandwidth and effective utilization of RIS-reflected wave communication resources. RIS-MIMO waves can bring the advantages of high antenna gain, high link reliability, and high system capacity. However, increasing the number of antennas and many RIS elements will also lead to high hardware costs, high signal processing complexity, and high channel variability, which restricts its practical application. This work mainly focuses on the channel estimation scheme of the RIS-MIMO system, and the chapters of this thesis are arranged as follows:

Chapter I Introduction: Firstly, through the background, this thesis introduces the current situation of data demand and spectrum resources in short supply caused by the rapid development of wireless communication technology and extends the importance of developing RIS-MIMO systems. The problem statement explains and confirms some essential technical problems in developing the RIS multi-input and multi-output systems. According to the above, the three issues to be studied in this project are improving the accuracy of channel estimation, reducing the effect of multipath fading of the incident and reflected signals, and considering how to control phase shift and beamforming of the reflected signals. Then, it discusses the purpose of the implementation of the project and describes the specific expected objectives. Finally, the research scope involved in this thesis and the plan outline are also mentioned.

Chapter II Literature Review: In this part, the research status of the RIS-MIMO system and the commonly used channel estimation methods are discussed in detail. This part discusses the current situation of cascaded channel estimation, analyzes the challenges and future development of channel estimation, and obtains appropriate ways suitable for the project, further proving the project's importance. It provides a practical and essential reference value for researchers in related fields.

Chapter III Methodology: In this part, how to model the channel as a 2D image and the simulation setup parameters of the scenario, system, and channel model in the RIS-MIMO system are introduced in detail. Next, we present the design of a deep learning model to facilitate the optimal phase shift and high-capacity data-rate communication systems.

Chapter IV Results and Discussion: Aiming at the goal of this project, this chapter successively proposes a deep learning channel estimation algorithm to improve the accuracy of channel estimation in the RIS-MIMO system. An SRIR-ChNet structure is adopted to solve the low-resolution image and noise problems caused by multipath fading. Also, multiuser high-dimensional complex operations can obtain channel parameter estimation accurately and an optimal phase shift matrix with the help of a proposed PS-CNN and BA-CNN. Simulation experiments verify the centralized algorithms presented above.

Chapter V Conclusion and Future Works: Finally, the thesis is summarized. Then, several research issues and directions are suggested for further investigation in the RIS-MIMO system.

CHAPTER 2

LITERATURE REVIEW

This chapter offers a concise overview of channel estimation techniques for wireless communication systems, focusing on conventional Reconfigurable Intelligent Surfaces (RIS) currently employed in 5G networks and proposed for 6G. It describes the RIS-MIMO framework within both uplink and downlink transmission systems, highlighting existing research on channel estimation techniques developed for RIS-MIMO. Finally, the chapter concludes with a summary of this overview and identifies the research gaps.

2.1 Introduction

With the increasing demand for high-speed wireless communication and the need for enhanced quality of service (QoS), accurate channel estimation has become a critical challenge in modern networks. Reconfigurable Intelligent Surfaces (RIS) have emerged as a promising technology to improve signal propagation and spectral efficiency in MIMO systems. In recent decades, researchers have focused on enhancing wireless channel QoS while seeking low-energy technologies. As 5G faces limitations in connection capacity and energy efficiency, the development of sixth-generation (6G) technology has garnered significant interest [25]. The advancement of 5G technology is nearing its limitations, while the growing demands of the IoT era necessitate enhanced spectral efficiency and overall system performance. Massive MIMO, a fundamental technology for both 5G and next-generation 6G networks, relies

on multiple RF antennas, resulting in substantial hardware and maintenance costs. Moreover, the limited propagation range and coverage of high-frequency electromagnetic waves necessitate the deployment of additional base stations, further escalating operational expenses. Additionally, the high concentration of base stations and antennas intensifies signal interference, degrades network performance, and complicates system coordination. This creates significant challenges for 5G development, highlighting the need for effective solutions for the future of 6G [26,27].

Several strategies have been suggested to ensure enhanced performance and sustainability in 6G. RIS consists of numerous passive reflective elements that dynamically reshape the wireless communication environment by digitally controlling electromagnetic waves. This allows for modifications in amplitude, phase, and frequency, thereby enhancing overall system performance [28,29]. In 5G networks, millimeter waves (mmWave) serve as a crucial solution for increasing communication capacity and mitigating spectrum shortages. However, their short wavelengths present significant transmission challenges [30]. The deployment of RIS can effectively enhance signal coverage. Before the advent of RIS, several techniques, including active frequency-selective surfaces, were developed [31]. The development of RIS technology [32] was built upon earlier innovations, including space-time-modulated digital coding metasurfaces. By adjusting phase shifts to facilitate passive beamforming, RIS significantly improves network capacity [33]. RIS technology has advanced with the development of both reflective and transmissive RIS, the latter ensures improved aperture efficiency along with a broader operational bandwidth [34]. Furthermore, RIS offers significant advantages in low power consumption and cost, especially compared to amplify-and-forward relays, because its components operate passively [35]. These features make RIS particularly well suited for high-frequency

bands, OFDM applications [36], NOMA [37], and multi-antenna systems. Accurate channel state information (CSI) is essential for wireless communication systems to function efficiently and reliably; therefore, accurate channel estimation is a crucial but challenging task. Extensive research has been dedicated to this issue, This thesis offers a comprehensive analysis of channel estimation techniques based on RIS.

2.2 Towards 6G: TeraHertz Communications

Motivated by the rapid worldwide rollout of 5G wireless systems, researchers across industry and academia are now actively investigating technological advancements for the upcoming 6G networks. The significant growth of mobile subscribers and wireless devices, along with new applications like augmented reality (AR), industrial automation, and the tactile Internet, may lead to capacity and performance limitations in 5G. Driven by the need to satisfy the growing demands of the Internet-of-Everything (IoE) [38]–[39], significant research efforts are underway in the area of 6G technologies. In response to these challenges, the International Telecommunication Union (ITU) recently established the Focus Group on Technologies for Network 2030 (FG NET-2030) to explore use cases and technologies relevant to 6G development [40]. The core 5G services include Enhanced Mobile Broadband (eMBB) enabling data transmission speeds of up to 1 Gbps, ultra-reliable low-latency communication (URLLC) with 99.999% reliability and millisecond latency, and massive machine-type communication (mMTC) supporting around one million devices per square kilometer in IoT networks [41]–[42]. Unlike 5G, 6G aims to enhance all network aspects data rate, latency, energy efficiency, and reliability while shifting from basic connectivity to connected intelligence, by combining communication, computing, control, sensing,

and AI-driven learning enables the definition of 6G's key performance indicators (KPIs), which are outlined in reference [38]–[39], [43]–[44]:

- **Peak Data Rate:** A maximum data rate of 1 Terabit per second (Tbps) is targeted for both indoor and outdoor scenarios under optimal wireless propagation conditions, signifying a performance increase of 100 to 1000 times relative to 5G.
- **User Data Rates:** The objective is to achieve user-experienced data rates of 1 Gbps for downlink and 500 Mbps for uplink, signifying a tenfold enhancement compared to 5G performance.
- **Bandwidth:** The frequency bands for Millimeter-wave (mmWave) are capable of supporting up to 10 GHz, while terahertz (THz) and visible light frequency bands can reach up to 100 GHz.
- **Energy Efficiency:** A 10 to 100 times increase over 5G to support sustainable communication and decrease the overall power demands of the network.
- **Spectral efficiency:** Optimizing the use of the frequency spectrum through advanced antenna and modulation techniques, five times higher than 5G.
- **Connection density:** 10^7 devices per km^2 to enable massive connectivity in the Internet of Everything (IoE) and enhance massive Machine Type Communication (mMTC), approximately 10 times higher than 5G.
- **Reliability:** The reliability is around 99.99999% to provide even better ultra-reliable low-latency communication (URLLC) compared to 5G.
- **Air-interface latency:** A latency of 100 μs to enable improved ultra-reliable low-latency communication (URLLC) and support emerging Internet of Everything (IoE) applications such as augmented reality (AR), mixed reality (MR), and virtual reality (VR), surpassing 5G capabilities.
- **Positioning accuracy:** In three-dimensional (3D) space, centimeter (cm)-level positioning accuracy is required to meet the increased demands of various vertical and industrial applications. In contrast, the requirement for 5G is limited to achieving accuracy on the order of meters within a 2D plane.
- **High-Speed Mobility:** Ensure reliable communication in high-mobility contexts, accommodating maximum speeds of up to 1,000 km/h for platforms like high-speed trains and aircraft. Table I presents a comparison of the key performance indicators (KPIs) targeted for 5G and 6G.

Table 2.1: Analyzing the Differences in Major KPIs between 5G and 6G [38,39], [43,44]

KPIs	Peak data rate	User-experienced data rate	Maximum bandwidth	Energy efficiency	Spectral efficiency	Connection density	Reliability	Air-interface latency	Positioning accuracy	Mobility
5G	≥ 1 Gbps	Downlink: ≥ 0.1 Gbps Uplink: ≥ 50 Mbps	1 GHz	10-100 $\times$ over 4G	3 $\times$ over 4G	10 ⁶ /km ²	99.999%	1 ms	m-level (2D)	500 km/h
6G	≥ 1 Tbps	Downlink: ≥ 1 Gbps Uplink: ≥ 500 Mbps	100 GHz	10-100 $\times$ over 5G	5 $\times$ over 5G	10 ⁷ /km ²	99.99999%	10-100 μ s	cm-level (3D)	1000 km/h

In the past decade, significant efforts have been made to advance several key technologies for 5G, including millimeter-wave (mmWave) communication and massive multiple-input multiple-output (MIMO)[41]–[42]. These technologies have played a crucial role in improving 5G performance. However, these advancements also face challenges, including rising energy consumption and high hardware costs. For example, to enhance spectral efficiency, massive MIMO requires numerous active antennas and radio-frequency (RF) chains for its operation, which in turn increases energy consumption and costs, potentially hindering large-scale deployment. Although mmWave communication provides higher bandwidth for increased capacity, it is prone to issues such as blockage and absorption loss, requiring expensive antennas and complex signal processing to address propagation loss, an approach that may not be scalable for 6G. Network densification, by adding more cell sites, enhances coverage and capacity, but this approach also presents difficulties, resulting in increased energy usage and greater deployment costs due to the proliferation of active nodes, like small-cell base stations, that are added. Furthermore, excessive densification can cause severe interference, complicate resource management, and create demanding backhaul requirements. The unpredictable character of the wireless propagation environment, leading to channel fading and signal distortion, presents a major obstacle to realizing ultra-reliable and high-capacity wireless communication systems, ultimately affecting performance negatively. Addressing the challenges of wireless unpredictability has led to significant research [45][46] into adaptive strategies such as modulation/coding, diversity, equalization, power/rate control, and active beamforming, all aiming to mitigate fading or adapt. However, the inability of these transceiver-based techniques to control the random wireless environment directly hinders their capacity to reliably meet the stringent QoS demands of 6G,

particularly concerning continuous connectivity. As a result, there is an urgent need for new and disruptive wireless technologies that can efficiently and sustainably meet the KPIs of 6G. Reconfigurable Intelligent Surfaces (RIS) have emerged as a promising solution to create smart and adaptable wireless environments. RIS is a metasurface controlled digitally, consisting of many passive reflecting elements that use minimal power while modifying the phase shifts and amplitudes of incoming signals. Diverging from traditional wireless communication methods, RIS possesses the unique ability to actively manipulate the wireless propagation channel. This allows it to enhance signal transmission, for example, by increasing received signal strength for desired users and reducing interference for others [47, 48]. Consequently, RIS represents a novel and economically viable strategy for achieving 6G KPIs. The technology holds significant promise for enabling diverse and attractive functionalities that can yield substantial performance improvements for 6G, including:

1. The creation of a virtual line-of-sight (LoS) path helps to overcome signal blockages between communication devices, thus extending coverage for seamless connectivity and enabling the achievement of ultra-high data rates.
2. Augmenting the number of controllable signal paths between transceivers in multi-antenna/broadband systems to enhance channel power and rank, thereby increasing spatial multiplexing gain and spectral efficiency.
3. Achieving ultra-reliable communications involves modifying the statistical properties of the channel, for example, by changing problematic Rayleigh/fast fading channels (common in high mobility) into more beneficial Rician/slow fading channels.
4. To improve the QoS experienced by users, co-channel and inter-cell interference can be effectively eliminated or suppressed, while at the same time strengthening the received quality of the target signal.
5. Supporting massive connectivity affordably through enhanced connection density, which circumvents the requirement for a high concentration of power-hungry active BSs/APs.
6. Improving the precision of positioning in vertical and industrial applications by leveraging managed signal reflections and acting as a local reference for sensing tasks.

2.3 Channel Fading Models for 5G and Beyond

In a typical terrestrial propagation scenario, radio signals encounter various obstacles such as human bodies, trees, buildings, and mountains. These obstructions impact the signal through mechanisms like reflection, refraction, and scattering. Based on the distance relative to the wavelength of the signal, variations in signal strength can be categorized into three types: (i) path loss, which refers to gradual reductions in signal strength over long distances, (ii) shadowing, which results from large obstructions like buildings or hills blocking the signal, and (iii) fading, which involves rapid changes in signal strength due to multipath propagation and relative movement between the transmitter and receiver [49]. Small-scale fading results from signals arriving at the receiver via multiple paths, each with varying amplitudes, delays, and phases, over a spatial distance smaller than the radio wavelength or within a short time frame. This phenomenon, known as multipath propagation, occurs when radio signals travel along two or more paths before reaching the receiving antenna. The combination of these signals can either amplify or weaken the overall signal depending on their relative phases and amplitudes. The variation in total received signal strength is termed multipath fading, often used interchangeably with small-scale fading. Fading in wireless environments is generally classified into two types: slow and fast fading, influenced by the relative movement of the transmitter and receiver or nearby reflecting objects. Additionally, fading can be categorized by frequency into flat fading and frequency-selective fading. Frequency-selective fading occurs when only part of the signal bandwidth is affected, while flat fading refers to cases where the signal bandwidth is smaller than the range of frequencies impacted by fading. System designers must consider the effects of multipath fading and noise on mobile channels

when designing telecommunications networks. The following section presents key classical and generalized fading models.

2.3.1 Small-Scale Fading Models

In this section, the classic models of fading and some of the new models of fading will be reviewed.

2.3.1.1 Rayleigh

Rayleigh fading is typically used to model NLOS scenarios where there is no dominant direct path between the transmitter and receiver. It is characterized by multipath propagation, leading to rapid fluctuations in signal amplitude. Mathematical Representation: The envelope of the received signal follows a Rayleigh distribution[50]:

$$p(r) = \frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}}, \quad r \geq 0 \quad (2.1)$$

where r is the amplitude of the received signal and σ^2 is the variance of the multipath components. In NLOS conditions, Rayleigh fading can lead to significant variations in signal strength, necessitating techniques such as diversity combining to mitigate its effects. For example, the level crossing rate (LCR) is higher in Rayleigh fading compared to Rician fading due to the absence of a strong LOS component.

2.3.1.2 Rician

Rician fading applies to scenarios where a strong direct path exists alongside multiple scattered paths. This model is relevant in environments with a clear line of sight, such as urban areas or indoor settings. Mathematical Representation: The Rician distribution can be expressed as [50]:

$$p(r) = \frac{r}{\sigma^2} e^{-\frac{(r^2+A^2)}{2\sigma^2}} I_0\left(\frac{Ar}{\sigma^2}\right), \quad r \geq 0 \quad (2.2)$$

Where A is the amplitude of the direct path component, and $I_0(\cdot)$ is the modified Bessel function of the first kind. Rician fading provides better performance than Rayleigh fading due to the presence of a strong LOS component. The average fade duration for Rician fading is shorter than that for Rayleigh fading, making it more suitable for applications requiring reliable communication.

2.3.1.3 AWGN

AWGN represents random noise added to signals during transmission. It assumes that noise samples are independent and identically distributed (i.i.d.) Gaussian random variables. Mathematical Representation: The received signal can be modeled as[50]:

$$y(t) = x(t) + n(t) \quad (2.3)$$

where $y(t)$ is the received signal, $x(t)$ is the transmitted signal, and $n(t)$ represents AWGN with zero mean and variance $N_0/2$. AWGN serves as a baseline model for

evaluating system performance under ideal conditions without multipath effects. It is often combined with fading models to assess overall system performance.

In summary, the choice of a fading model for a RIS-MIMO system depends on the specific propagation environment and the presence or absence of a dominant LOS component. Rayleigh fading is suitable for NLOS scenarios, while Rician fading is more appropriate for scenarios with a strong LOS component. AWGN is a common noise model that affects all types of channels.

2.4 Cascaded and Separate Channel Estimation based on CNN for RIS-MIMO System

RIS is considered one of the most promising methods for obtaining CSI. The field of RIS technology is known by several different names, such as reconfigurable intelligent surfaces, intelligent walls, bright reflect arrays, low-cost integrated wall devices, and software-controlled metasurfaces. Despite the different terminology, these research areas all focus on developing novel radio environments using RIS technology with diverse functionalities. RIS can be classified into active and passive surfaces based on their ability to amplify and process incoming radio waves. Additionally, surfaces can be categorized as monostatic or dynamic/reconfigurable, depending on their functionality. This thesis examines nearly passive and active RIS elements, which are comprised of affordable metallic or dielectric flat surfaces with many passive reflectors. These elements manipulate wireless communication by adjusting the phase shifts of incoming signals [61,62]. Various techniques are being investigated to implement RISs, with several methods proposed for reconfiguring reflection coefficients, including the use of PIN diodes [63], varactor diodes [64], MEMS

switches [65], liquid crystals [66], and graphene [67]. The reflection phase of a PIN-loaded reconfigurable element is determined by the on/off state of its PIN diode, with a single diode providing two distinct phase states (1-bit quantization). Varactor diodes are employed to achieve continuous phase shifts [68]. For millimeter-wave applications, MEMS switches offer advantages over PIN diodes due to lower insertion losses [69]. While graphene [70] and liquid crystals [71] enable continuously adjustable reconfigurable reflect arrays at higher frequencies (millimeter/sub-millimeter waves), their significant losses [72,73] make them less practical for designs operating at lower frequencies. The RIS, comprising a matrix of N smart reflective elements, enables dynamic signal control through phase shifter adjustments. In some cases, amplitude modulation is also utilized to offset incoming signal loss.

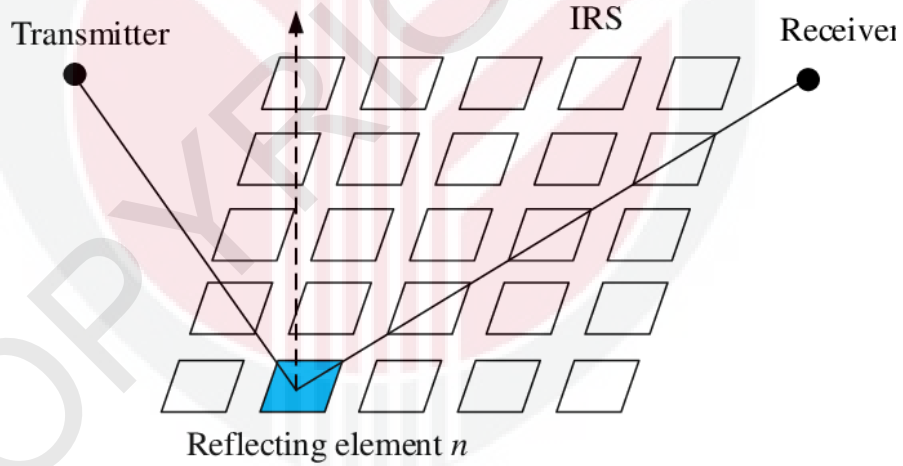


Figure 2.1: A RIS surface containing multiple discrete reflecting elements[74]

RIS can be constructed from an advanced adaptive (smart) thin composite material sheet, similar to paper, that can cover parts of walls, buildings, and obstacles. This sheet can modify the radio waves that interact with it, with programmable modifications controlled by external stimuli, the phase and amplitude of the signal

incident on each radiating element can be precisely adjusted, enabling the propagation of signals to be guided as desired. A key feature of RISs is their reconfigurability after deployment in a wireless environment. RIS operation generally involves two distinct phases, which are repeated at intervals determined by the environment's coherence time [75].

- i. **The Control and Programming:** This phase involves gathering environmental information needed to determine the RIS's operational parameters, which are then used to configure the RIS for subsequent operation.
- ii. **The Communication:** This phase is when the configured RIS actively contributes to device-to-device communication within the network. Reflect arrays and metasurfaces are the fundamental architectural designs for RIS.

While RIS can be designed in various ways, the primary implementation methods involve reflect arrays and metasurfaces [76].

1. **Reflect array-based RIS:** A basic method for constructing a reconfigurable intelligent surface involves employing a passive planar reflect array, as shown in Figure 2.2. In this setup, the antenna termination is electronically adjustable, allowing for the modification of the incoming signal's phase and its precise reflection. It's important to note that a considerable number of antennas is essential at elevated frequencies to cover even limited surface areas. To illustrate the high density required, operating at a 28 GHz central frequency common in 5G systems necessitates roughly 10,000 antennas to provide coverage over only a single square meter.
2. **Metasurface-based RIS:** This type represents a more advanced way to construct an RIS, achieved by employing metasurface technology [76], which can be understood as two-dimensional analogs of metamaterials. Metamaterials are engineered materials with electromagnetic properties that do not occur naturally. Metasurfaces consist of numerous closely packed, sub-wavelength resonant structures known as pixels or meta-atoms.

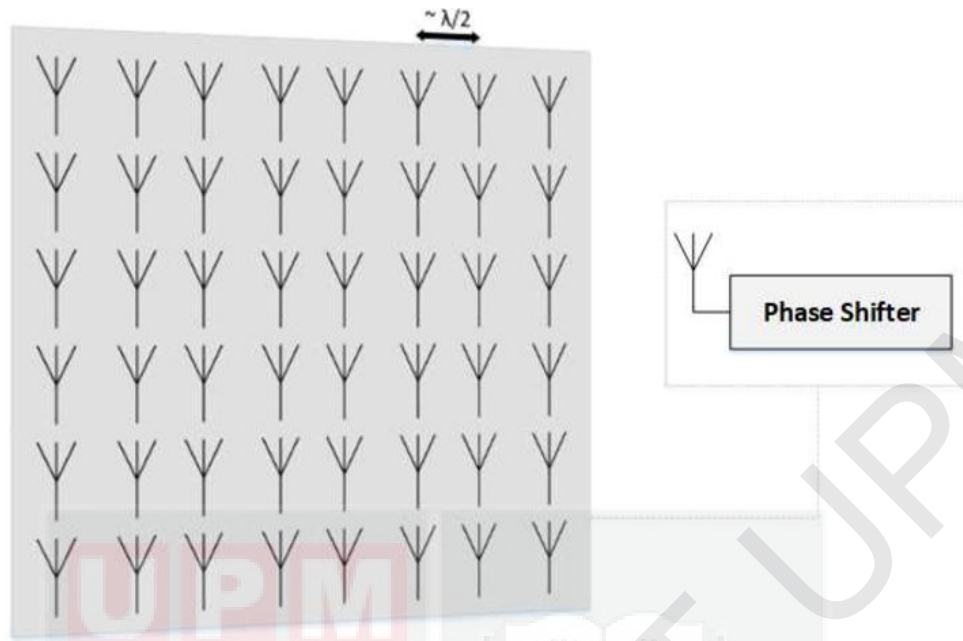


Figure 2.2: A reflect-array comprising 48 elements, each consisting of a traditional antenna connected to a phase shifter[76]

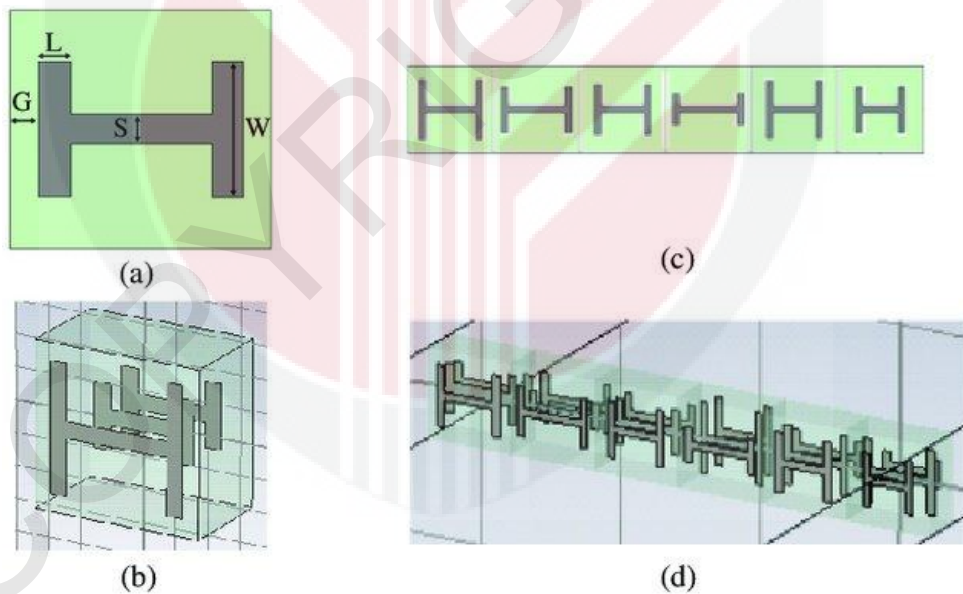


Figure 2.3: Metasurface scattering particle details: (a) Front view of a unit cell, the dog-bone-shaped metallic particle. (b) Perspective view of the unit cell, with dielectric substrates rendered transparent for visualization. (c) Front view of a supercell composed of 6 unit cells. (d) Perspective view of the supercell [77]

Individual meta-atoms (or unit cells, see Figure 2.3) and the spaces separating them are far smaller than the operational wavelength. The dimensions of these meta-atoms and

the tile's thickness act as crucial design constraints, determining the upper frequency limit for interacting with EM waves. As noted in [65], meta-atoms typically occupy a square area ranging from $[\lambda/10 - \lambda/5]$. The minimum thickness of a metasurface is also within the range of $[\lambda/10 - \lambda/5]$. To enable a metasurface to be reconfigurable, it must incorporate dynamic meta-atoms, which can adjust their electromagnetic characteristics concerning time as in Figure 2.4.

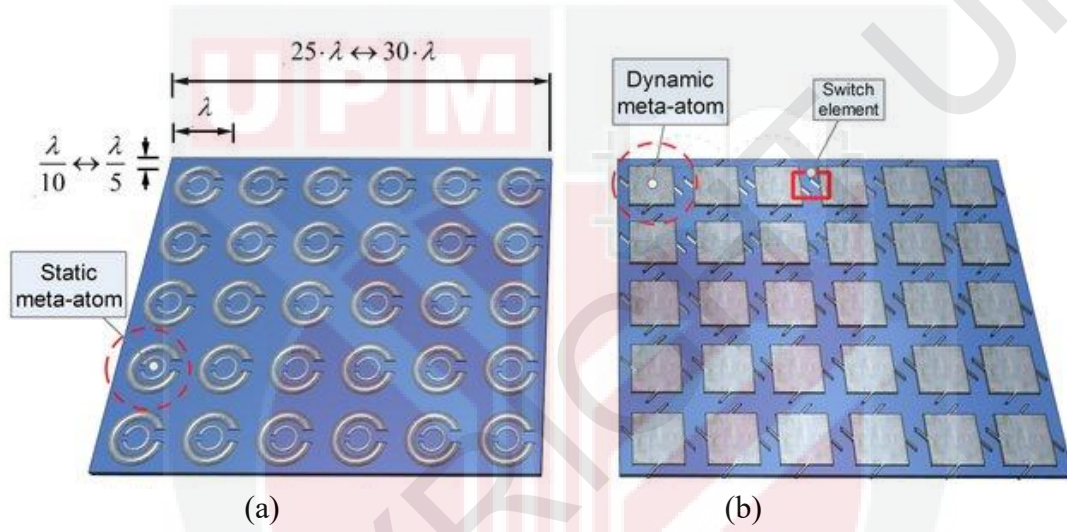


Figure 2.4: (a) Static metasurface (b) Dynamic metasurface: dynamic control, one advantageous, low-cost, and easily scalable approach is to manage the metasurface switches as a diode array[77]

While the small size and dense packing of meta-atoms offer numerous control options for electromagnetic waves, existing research primarily concentrates on reflectarray-based RIS, which has yielded significant results. A common simplification in RIS linear channel models is the disregard for signal coupling between neighboring elements. In real-world scenarios, a higher number of reflecting elements within a given RIS surface area results in improved passive beamforming and better system performance. However, this reduction in element spacing can intensify mutual coupling, making it more significant. As a result, nearby reflecting elements may interact through circuit coupling, leading to

coupled reflection coefficients. According to [74], the literature presents three primary methods for reconfiguring RIS elements, all aimed at achieving precise reflection control :

- i. Mechanical actuation, including physical rotation and translation of the RIS, is one approach to reconfiguration.
- ii. Materials with specific functional properties, like liquid crystal and graphene, are employed for RIS reconfiguration.
- iii. Electronic devices, such as positive-intrinsic-negative (PIN) diodes, field-effect transistors (FETs), or micro-electromechanical system (MEMS) switches, are also used for reconfiguration.

The third method, illustrated in Figure 2.5, is commonly used in practical applications for both reflectarray and metasurface-based RIS. Its popularity stems from its rapid response, low reflection loss, and relatively low energy and hardware requirements. As depicted in Figure 2.5, this method commonly utilizes a three-layer structure combined with a smart controller.

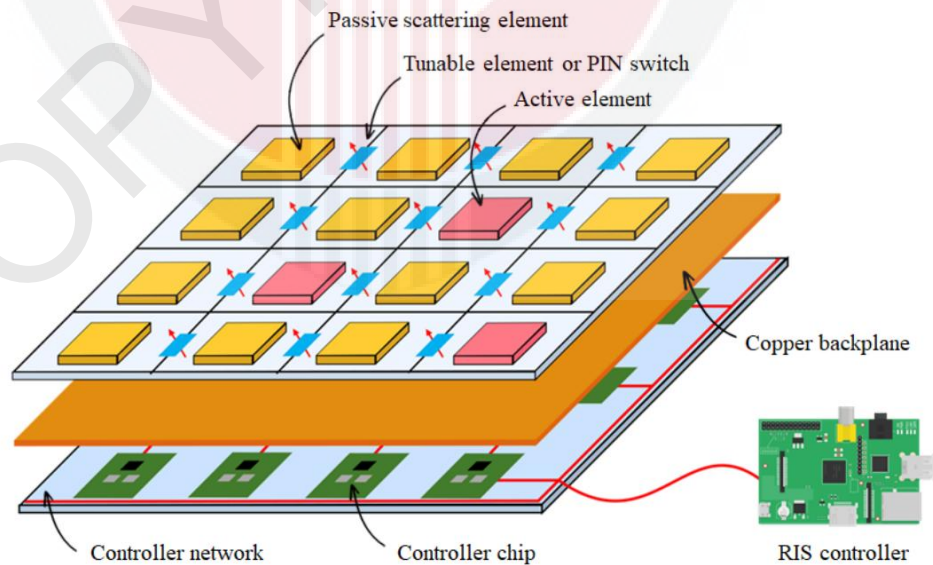


Figure 2.5: An example of a standard RIS architecture that uses electronic control methodscontrol [76]

The outermost layer, which directly interacts with incident signals, is composed of numerous tunable metallic patches printed on a dielectric substrate. The intermediate layer, usually a copper plate, serves to minimize signal energy leakage during reflection by the RIS. The third (inner) layer houses a control circuit board that manages the activation of the reflecting elements and adjusts their reflection amplitudes and/or phase shifts in real-time. This reflection adjustment is overseen by a smart controller, typically implemented using a field-programmable gate array (FPGA), which is connected to each RIS. The structure of an individual element, as depicted in Figure 2.6, features an embedded PIN diode that enables control.

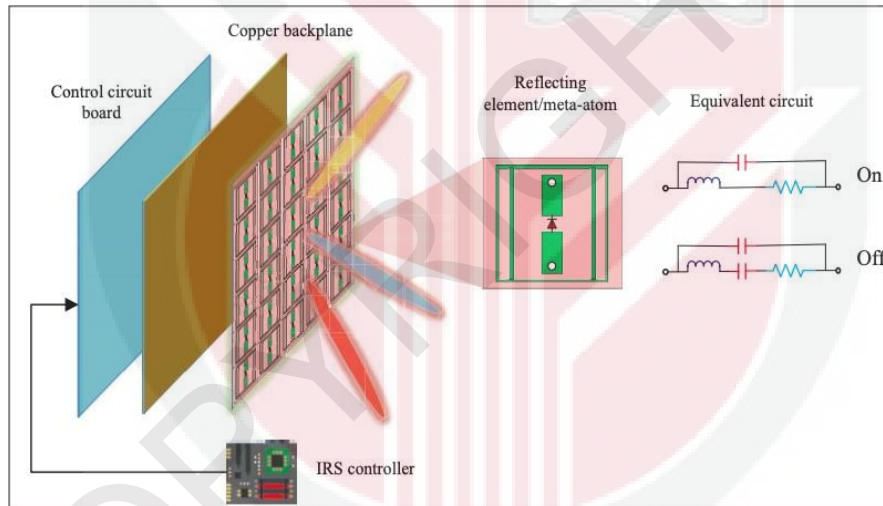


Figure 2.6: An example of a reflecting element made tunable through the use of a PIN diode[78]

Adjusting the bias voltage via a DC feed line toggles the PIN diode's state ('ON'/'OFF'), resulting in a π radian phase shift illustrated by the equivalent circuits. This diode-based control applies to both reflectarray and metasurface RIS designs. For metasurfaces, this control is embedded within a more complex structure (Figure 2.7). Here, a meta-atom functions as a supercell composed of multiple units, similar to the configuration shown in Figure 2.3.

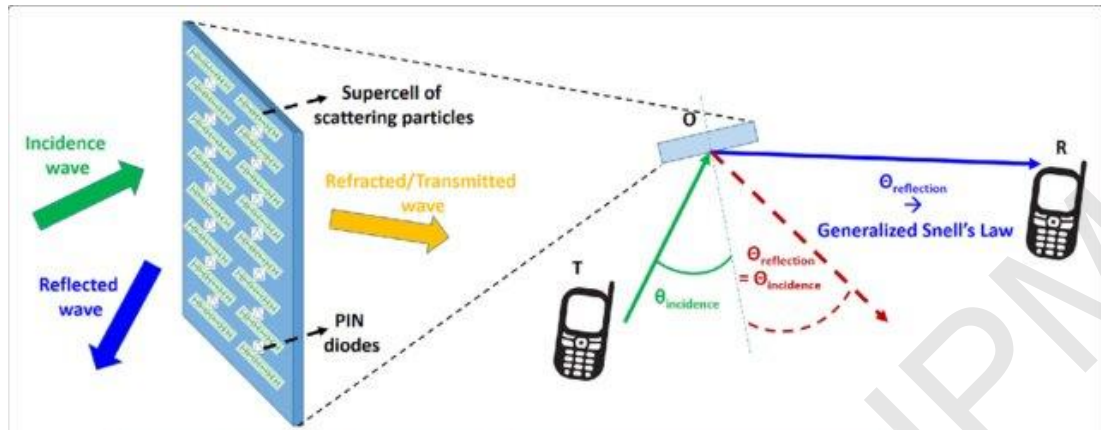


Figure 2.7: Reconfigurable metasurface utilizing dynamic supercells [79]

Control via a diode array is simple, requiring wiring between switches and the gateway. With PIN diode switching frequencies reaching 5 MHz (corresponding to 0.2 μs switching time), it significantly outpaces standard channel coherence times (ms). This makes it well suited for dynamic mobile scenarios. However, the ability to continuously tune both amplitude and phase on every RIS element is advantageous for communication systems, reference [74] points out that this fine-grained control can be costly to implement. The requirement for advanced design techniques and costly hardware is inherent in the production of high-precision elements, potentially hindering scalability as the number of elements increases. Specifically, implementing 16 phase shift levels necessitates four PIN diodes per element, which presents considerable design challenges given the size constraints of individual elements. Moreover, this configuration requires the RIS controller to have a higher number of control pins to manage the extensive array of PIN diodes. Since practical RISs generally contain numerous elements, implementing discrete amplitude/phase shift levels is ultimately more economical. To lessen the amount of control data needed for each element, this method utilizes a minimal number of bits. For example, a single bit can

manage amplitude, allowing for either reflection or absorption, and two bits can handle phase shifts, specifically 0 or π radians. Further reductions in hardware costs and design complexity are achieved by implementing either discrete phase-shift or amplitude control, yielding two simplified discrete model variants:

- i. This RIS configuration allows for the adjustment of each reflecting element's phase shift while maintaining a fixed, maximum reflection amplitude of one, effectively implementing discrete phase-shift control only.
- ii. This particular RIS design enables control over the reflection amplitude of individual elements, while their phase shift remains constant, often set to zero for simplicity, effectively implementing discrete amplitude control only.

Implementing phase-shift control, also known as phase beamforming, in Reconfigurable Intelligent Surfaces (RIS) typically comes at a higher cost compared to amplitude control or amplitude beamforming. However, when the same number of control bits or discrete levels is applied to each reflecting element, phase-shift control provides superior passive beamforming performance over amplitude control. While the ability to independently control both the reflection amplitude and the phase shift offers the most extensive design flexibility, it also introduces significant challenges in the design of the unit cell.

2.4.1 Signal Processing Algorithms for RIS Channel Estimation

Despite the advantages of Reconfigurable Intelligent Surfaces (RIS), several practical challenges must be addressed in RIS-MIMO wireless communications. Key difficulties lie in estimating the RIS channel and designing passive beamforming when only partial channel state information (CSI) is available, and dealing with different hardware constraints. Accurate CSI acquisition is essential but challenging for two main reasons: Passive RIS elements cannot easily transmit or receive pilot signals for

accurate channel estimation because they lack the necessary active components for baseband signal processing. Second, the large number of passive elements in an RIS leads to increased system overhead due to differing channel coefficients. Furthermore, the wide range of system configurations and deployment scenarios such as variations in user count (single/multi), RIS deployment (single/multi), antenna numbers (single/multi at BS/user), user mobility (low/high), and bandwidth (narrowband/broadband) creates diverse needs for channel estimation. To address these varied requirements, channel estimation algorithms are typically grouped into several categories: conventional, optimization, compressive sensing (CS), deep learning, and composition algorithms.

2.4.1.1 The Conventional Algorithms

In the conventional method of channel estimation, a predefined model is used to estimate the channel matrix. The transmitter sends a pilot signal, and the receiver records the corresponding signal.

1. **LS/LMMSE:** Least Square (LS) estimation [80] and Linear Minimum Mean Square Error (LMMSE) are classical methods used for channel estimation, providing model-based solutions. These techniques are utilized in RIS systems for estimating the channel matrix based on pilot signals. However, traditional channel estimation-based RIS approaches, such as LS and LMMSE, suffer from high pilot overhead. To minimize channel estimation errors for these algorithms, researchers [81, 82] have proposed simultaneously optimizing the training reflection pattern and the transmitted pilot sequence. The conventional LS estimation encountered significant pilot

overhead, which was addressed by [83]. By leveraging a low-rank subspace, a refined least square estimation approach with a reduced subspace and an optimized phase shift-based RIS pattern was introduced to reduce the mean square error (MSE) to estimate the channel matrix. Xu et al. [84] employed MMSE channel estimation for UAV applications; this includes optimizing the RIS phase shift matrix with a simple method to enhance system performance while reducing computational complexity. However, at high Doppler frequencies, traditional RIS-based channel estimation methods typically depend on block fading models, where the channel remains constant over a block of time before changing in the next interval. In [85], increased estimation overhead was attributed to Doppler frequency shifts in time-varying channels. A correlation coefficient linking the LoS and NLoS components was then introduced as a way to reduce the computational complexity. Additionally, a channel model was developed to improve the MMSE estimation, leading to greater precision.

2. Grouping RIS: A performance improvement was achieved by grouping RIS elements to reduce training and leverage spatial channel correlation [86]. This method involved dividing a large RIS into smaller groups, where each group maintained identical reflection coefficients. This approach gained widespread adoption in later channel estimation-based RIS techniques. In an uplink RIS-MIMO multi-user (MU-MIMO) system, [87] addressed channel estimation by dividing the RIS surface into smaller sub-RISs and then applying an estimation method that utilizes the SPD matrix.

3. Kalman filtering (KF): This enables channel estimation across multiple time blocks, assuming the channel coefficient matrix remains constant over the coherence time [88]. To address mobile settings, Mao et al. [89] utilized Kalman Filtering (KF)

and determined RIS reflection coefficients by minimizing the Mean Square Error (MMSE). For frequency division duplex MIMO downlink systems, [90] presented a method that estimates direct and cascaded channels through the application of two distinct Kalman Filter (KF)-based tracking algorithms. Their technique involved approximating the ideal coefficient matrix using column selection from the DFT matrix and concurrently optimizing the reflection coefficients throughout the pilot and RIS stages.

4. Multi-stages: To achieve higher accuracy in RIS channel estimation, the distributed multi-stage algorithm has become a commonly adopted method. Accurate channel estimation with minimal pilot overhead is desired. To that end, a multi-stage, multi-user wideband scheme for cascaded channel estimation is proposed. In the method proposed by Qian et al. [91], the first step is to estimate the BS-RIS CSI using a combination of cyclic prefix single-carrier transmission and manipulation of the phase shift reflection coefficients. The subsequent step entailed deriving the cascaded channel information in the frequency domain, utilizing only a portion of the BS-RIS channel states. Table 2.2 categorizes conventional channel estimation algorithms using four principal dimensions for comparison: antenna/RIS architecture, channel model, major algorithm, and performance analysis.

Table 2.2: Comparison of conventional algorithms for RIS channel estimation

Ref.No.	Year	System Model	Channel Model	Algorithms	Performance Enhancement Summary
Zhou et al. [80]	2021	MIMO/Passive RIS	Quasi static channel	AoA estimation and LS method	Achieves improved estimation accuracy over existing methods while keeping pilot overhead low.
Demir et al. [83]	2022	MIMO/Passive RIS	Quasi static channel	Reduced-subspace LS and array geometry	Reduces eNMSE to -40 dB at an SNR of 0 dB.
Xu et al. [84]	2022	SISO/Passive RIS	Time-varying and double-selective channel	MMSE and the end-to-end system model	Effectively decreases the required transmission power for distances ranging from 140 m to 800 m.
Shtaiwi et al. [87]	2021	MIMO/Passive RIS	Quasi static channel	SPD and Maximum-margin matrix factorization	Improves performance by up to 6 dB as the sub-RIS size increases.
You et al. [88]	2020	MIMO/Passive RIS	Time-varying channel	RIS-elements grouping and partition	Achieves performance nearly equivalent to the phase shift method when using three-bit quantization.
Mao et al. [89]	2021	MIMO/Passive RIS	Time-varying channel	MMSE, KF, and state-space model KF and codebook-based low-complexity design	Exhibits superior BER performance compared to the MMSE estimator.
Cai et al. [90]	2021	MIMO/Passive RIS	Time-varying channel	MMSE interpolation and multiplicative	Reduces computational complexity while improving estimation accuracy.
Xu et al. [85]	2023	SISO/Passive RIS	High-dimensional and high-Doppler-reflected fading channels	concatenation of the channel coefficient	Minimizes the error floor while achieving higher data rates in high-mobility environments.
Qian et al. [91]	2023	MIMO/Passive RIS	Quasi static channel	Two-phase and anchor-aided channel estimation	Reduces pilot overhead while improving estimation accuracy.

2.4.1.2 Optimization-Based Algorithms

Optimization techniques play a crucial role in channel estimation based on RIS. The (GEM) Generalized Expectation-Maximization algorithm is employed to estimate the parameters when certain variables are unknown, iteratively improving both the model and its parameters to achieve an optimal solution. Several optimization-based approaches tackle RIS channel estimation. For instance, reference [92] employed a GEM-based spatially alternating technique, enhancing precision by identifying multipath components and using maximum likelihood (ML) estimation. Addressing a related challenge, reference [93] focused on determining the true phase shift matrix of RIS elements. They proposed a novel over-the-air (OTA) strategy, formulated as a complex high-dimensional optimization problem. An iterative algorithm yielded ML estimates with root mean square error (RMSE) close to the Cramer-Rao Bound (CRB), confirming the method's efficiency. Separately, Guo et al. [94] introduced an alternating optimization algorithm designed to decrease pilot training overhead. Their approach incorporates both common-link and user-specific variables, offering a computationally efficient, locally optimal solution for the inherent non-convex optimization task. Similarly, Lin et al. [95] treated the millimeter-wave channel estimation task as a non-convex optimization problem. They employed alternating minimization alongside manifold optimization techniques to find locally optimal solutions. Table 2.3 offers a detailed comparison of optimization-based channel estimation algorithms like this one, analyzing their methodologies and performance using categories such as antenna/RIS architecture, channel modeling, primary algorithms, and performance evaluation methods.

Table 2.3: A study compares different optimization methods for estimating channels in RIS systems

Ref.No.	Year	System Model	Channel Model	Algorithms	Performance Enhancement Summary
Xu et al. [92]	2022	MIMO/Passive RIS	Quasi static channel	Space-alternating GEM and ML estimation	Shown improved performance when the RIS was optimized using the ideal phase shift configuration.
Zhang et al.[93]	2023	SISO/Passive RIS	Quasi static channel	ML and CRB	Achieved phase estimates closely matching the Cramer-Rao Bound at an SNR of 20 dB.
Guo et al. [94]	2022	MISO/Passive RIS	Quasi static channel	Alternating RIS optimization	Delivered a performance gain of approximately 15 dB over the ON/OFF method.
Lin et al. [95]	2022	MIMO/Passive RIS	Quasi static channel	Alternating minimization and manifold optimization	Demonstrated superior performance compared to several state-of-the-art benchmark techniques.

2.4.1.3 Compressed Sensing-Based Algorithms

The problem is framed as an optimization algorithm commonly used in channel estimation for RIS [96], designed to accurately reconstruct the original signal from the sparse projection matrix with minimal distortion. The greedy algorithm, a popular approach in compressive sensing (CS), is widely used in signal recovery tasks due to its low computational complexity and efficient data reconstruction [97, 98]. Other prevalent CS methods, such as Atomic Norm Minimization (ANM) [99], Orthogonal Matching Pursuit (OMP) algorithm [100], Approximate Message Passing (AMP) [101], and tensor decomposition [102], have also been widely applied to the channel estimation process. The CS algorithm functions by progressively identifying the optimal transform base to sparsely represent the channel matrix, effectively transforming the process into an optimization problem. By utilizing minimal information, the channel matrix can be accurately estimated, which leads to a significant reduction in pilot training overhead during the channel estimation process.

1. OMP algorithm: The traditional Orthogonal Matching Pursuit (OMP) algorithm, when directly applied to RIS channel estimation, leads to high computational complexity. As a result, reducing training overhead has become an important topic of discussion. To manage the computational burden caused by the large number of RIS elements and the complexity of the composite channel, the channel estimation problem was recast as a sparse recovery problem, employing distinct dictionaries to represent angular and temporal channel characteristics. The multidimensional OMP strategy [103] for compressed channel estimation achieved a significant reduction in computational complexity by eliminating the need to compute

the large dictionary directly. To improve performance with multiple users, the algorithm was designed to recognize and use the joint sparse structure within the corner domain of the cascaded channels. In this domain, the matrices corresponding to various users contained common non-zero rows. By estimating the cascaded channels of multiple users in the common corner domain, the number of training samples was increased, which contributed to minimizing the noise effects.

2. AMP algorithm: The Orthogonal Matching Pursuit (OMP) algorithm sparsity is constant, which does not accurately represent real-world scenarios. To address this limitation, the Adaptive Messaging Passing (AMP) algorithm, which incorporates adaptive sparsity, was proposed. In [104], a two-stage algorithm was introduced, consisting of a matrix decomposition stage followed by a matrix completion stage. In [101], an initial estimation of the direct MIMO channel between User Equipment (UE) devices was done using conventional channel training. Subsequently, the dictionary matrix was determined using the bilinear adaptive vector approximation messaging algorithm. Lastly, during training, permutation ambiguity was addressed by utilizing the sparsity of the phase-shifted coefficient matrix. The analysis also considered the Central Limit Theorem (CLT) along with the statistical properties of the BS-to-RIS and RIS-to-user channel links, it was shown that sub-6 GHz channel propagation approximates a Gaussian distribution, enabling the use of the BiG AMP algorithm [105] for concurrent channel estimation and data detection. The pilot was employed to mitigate the effects of quantization as in the improved BiG AMP algorithm, utilizing a quantization-aware approach for Channel State Information (CSI) estimation. This method outperformed the approach presented in [101]. The interaction of row-sparse matrix elements caused some errors in traditional estimation methods using numerical

processing. In reference [106], a hybrid approximate message-passing method was suggested as a solution to this problem. To recover the row-sparse representation, the model employs a decomposition of the derivative frequency matrix. This method offers an improvement over the Generalized AMP (GAMP) algorithm, which faces challenges with non-Gaussian distribution dictionaries. In this section, we will review how Compressed Sensing (CS) algorithms are applied to RIS channel estimation and examine the problems associated with the conventional OMP algorithm, for example, its high computational burden and its dependency on a static sparsity value. To address the identified shortcomings, advanced research has introduced methods such as the joint adaptive sparsity AMP algorithm, which improves efficiency and lowers computational demands. A comprehensive overview of compressed sensing channel estimation algorithms, along with a comparative analysis of their performance, is presented in Table 2.4, which categorizes these methods according to antenna/RIS architecture, channel model, main algorithm, and performance analysis.

Table 2.4: A study compares compressed sensing methods for estimating channels in RIS systems

Ref.No.	Year	System Model	Channel Model	Algorithms	Performance Enhancement Summary
He et al. [104]	2020	MIMO/Passive RIS	Time-varying channels	Sparse matrix factorization and completion	Improved channel estimation precision beyond that of traditional techniques while simultaneously cutting transmission power by half.
Mirza et al. [101]	2021	MIMO/Passive RIS	Quasi-static channel	Bilinear generalized AMP	Outperformed the random algorithm by achieving a 3 bps/Hz increase in data rate.
Bayraktar et al. [103]	2022	MIMO/Passive RIS	Quasi-static channel	Multidimensional OMP	The system successfully localized 80% of users with a positional error of less than 20 cm.
Xiong et al. [105]	2023	MIMO/Passive RIS	Quasi-static channel	Bilinear generalized AMP	Performance was improved, notably with a faster convergence rate.
Zhou et al. [106]	2022	MIMO/Passive RIS	Quasi-static channel	Generalized-AMP	The number of training pilot symbols was decreased by one-sixth relative to the baseline scheme, achieving an eNMSE of 10^{-2} .
Wu et al. [107]	2022	MIMO/Passive RIS	Quasi-static channel	Three-step OMP	The proposed method requires 50% less pilot overhead than the baseline scheme, yielding an eNMSE of -16 dB.

2.4.1.4 Composition-Based Algorithms

The evolution of channel estimation algorithms has shown an increasing integration of deep learning techniques with conventional methods. Deep learning enhances the accuracy of channel estimation and enables the joint optimization of multiple system components, addressing the limitations of traditional algorithms. Furthermore, the advanced denoising capabilities of neural networks can significantly improve estimation accuracy, mitigating the shortcomings of conventional approaches.

1. **SemiDefinite relaxation (SDR)-deep learning:** The RIS elements are generally organized in a two-dimensional structure, enabling the channel information to be represented as one image. In their work, Yin et al. [108] first introduced a semidefinite relaxation (SDR) method and subsequently created a deep learning model for channel prediction, which determines the complete Channel State Information (CSI) from pilot data. This technique offers a substantial performance improvement, particularly in data rate, compared to conventional methods that group RIS elements.
2. **LS-deep learning:** To estimate channel information, Wang et al. [109] implemented the Least Square (LS) method. They then transformed the channel into a low-resolution image and utilized linear interpolation to produce a higher-resolution version.
3. **OMP-deep learning:** The traditional CS-OMP algorithm assumes precise grid alignment of arrival and departure angles during computation, which often doesn't hold in real-world scenarios, thereby limiting its effectiveness. However, this assumption

deviates from real-world conditions, leading to estimation errors. To resolve this issue, Mao et al. [104] integrated deep learning techniques into the OMP algorithm, specifically using a residual network to improve performance and estimation accuracy.

4. AMP-deep learning: The AMP algorithm, along with other traditional CS methods, reduces pilot overhead, but this comes at the cost of lower estimation accuracy. Tsai et al. [108] developed a learned AMP network supported by a hypernetwork, incorporating dynamic shrinkage parameters to improve this. Instead of using fixed shrinkage values, the network adapts its shrinkage parameters across layers, leading to improved estimation accuracy. Conventional approaches rely on human perception and problem modeling, followed by the development of an optimizer to refine the model. In contrast, deep learning methods leverage parameter fitting to tackle complex problems and can surpass traditional techniques when achieving effective convergence. Their capability to model a vast number of network parameters often exceeds that of conventional methods based on prior knowledge. As the complexity of problems grows, the benefits of deep learning become more evident, emphasizing the potential for integrating traditional solutions with deep learning techniques. A summary of composition-based channel estimation algorithms, including performance comparisons, is presented in Table 2.5. The methods are categorized by antenna/RIS architecture, major difficulties, and analysis of deep learning model performance.

Table 2.5: A study compares composition methods for estimating channels in RIS systems

Ref.No.	Year	System Model	Channel Model	Algorithms
Wang et al. [109]	2021	SISO/Passive RIS	High complexity of conventional algorithms	Using linear interpolation, a network with high resolution but low precision achieved 92% accuracy at a rSNR of 35 dB.
Mao et al. [110]	2022	MIMO/Passive RIS	Limited estimation performance of the CS algorithm	A residual network was designed to enhance estimation accuracy, demonstrating superior performance compared to the OMP method at an rSNR of 35 dB.
Tsai et al. [108]	2022	MIMO/Passive RIS	Insufficient performance of AMP algorithm estimation	A hypernetwork-assisted LAMP model, incorporating dynamic shrinkage parameters, was developed, resulting in a 50% reduction in memory usage and a 93% decrease in execution time.
Yin et al. [128]	2022	SISO/Passive RIS	Insufficient performance of conventional algorithm estimation	To decrease channel estimation overhead, an end-to-end deep learning model was designed.

2.4.1.5 Deep Learning-Based Algorithms

To estimate the channel based on RIS, deep learning has been widely utilized [112,113], taking advantage of neural networks' learning abilities to reconstruct the complete channel from partial pilot data [114,115]. To represent the RIS channel, image processing methods can be implemented, separating the channel information into two distinct images, one for the real and one for the imaginary components. With advancements in image processing, traditional interpolation and denoising methods have been applied to RIS channel estimation. In this method, raw channel information is first extracted and preprocessed before being fed into a neural network to obtain a precise CSI representation. The incorporation of image processing techniques has introduced a promising direction for enhancing CSI estimation, presenting opportunities for further exploration and development [116,117]. Most data used in channel estimation consists of complex numbers; however, existing deep learning libraries do not inherently support operations in the complex domain. As a result, a common preprocessing technique involves splitting the real and imaginary components of complex numbers before feeding them into the neural network. However, this method overlooks phase information, leading to significant data loss. To improve RIS channel estimation, deep learning methods utilize various network architectures, primarily categorized into six types: end-to-end models, convolutional neural networks (CNNs), graph attention networks (GANet), deep neural networks (DNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks.

1. **End-to-end network:** Typically, in existing RIS systems, tasks like coding,

modulation, channel estimation, equalization, decoding, and demodulation are handled independently. However, these functions can be integrated into a unified end-to-end network. This integrated approach can improve system performance by avoiding convergence to local optima. In [114], the transmitter, RIS, and receiver's connection weight coefficients are optimized together, aiming to reduce the system's cross-entropy loss.

2. CNN: For estimating both direct and cascaded channel estimation, Ahmet et al. [118] developed CNN networks, enabling users to directly access the network for their channel estimation. However, a major challenge emerged due to the large volume of coupled reflective surface channel information, which complicated the computation. To address the dynamic CSI tracking issue, [119] a compensated learning-based neural network was used. This deep learning approach directly learns fading channel characteristics, eliminating the need for prior knowledge, thanks to its high adaptability. Chen et al. [119] Further improved network performance by reducing hidden nodes and adding an offset learning module. In [104], Kundu et al. employed Convolutional Neural Networks (CNNs) for channel estimation by framing it as an image-processing task, achieving denoising and approximating optimal Minimum Mean Square Error (MMSE) solutions. By applying DReL to CNNs and using Bayesian estimation, they bypassed the complex integrals of MMSE, validating DReL's effectiveness. Combining the feature extraction and denoising strengths of CNNs and DReL resulted in a further improvement in channel estimation accuracy.

3. GANet: For channel estimation in full-duplex wireless communication links, Tekbiyik et al. [121] applied GANet. Their training results highlighted the robustness

of GANet across diverse propagation channels, showing superior performance over conventional LS estimation methods.

4. **DNN:** In [122], a three-step estimation method was developed, with an emphasis on direct channels, to determine channel coefficients for partially activated RIS elements. This method involved continuous training for both the active and passive RIS element cascade channels, resulting in high accuracy. In [123], Jin et al. addressed cascaded channels using residual neural networks and further proposed an online approach leveraging a multi-residual dense network to enhance performance.

To reduce pilot overhead, Zhang et al. [124] proposed an RIS grouping strategy with the assumption that all RIS elements within a group have identical reflection coefficients, as shown in Figure 2.8. This assumption does not accurately represent real-world conditions and can lead to some interference. To overcome these challenges, Zhang et al. [124] introduced a pair of deep learning networks, where the initial network focused on minimizing channel interference due to RIS grouping, while the second network focused on reconstructing the complete channel from partial channel data. The network, designed to process the real and imaginary components of the channel separately, consisted of three convolutional layers followed by residual blocks (RBs). Each RB was structured with three identical dense blocks (DBs), each containing five convolutional layers. The first four layers in each DB employed the leaky rectified linear unit (LReLU) for activation, and to facilitate information flow, feature maps from previous layers were forwarded to subsequent convolutional layers. The IENet output, represented as $\hat{\mathbf{A}}$, served to improve the precision of the partial

channel estimation. A constant, β , was used to scale the results of the nonlinear transformations, which were then summed with the initial input. The complete channel information was then generated by CENet, a network consisting of two convolutional layers and identical residual blocks (RBs), denoted as $\hat{A}$.

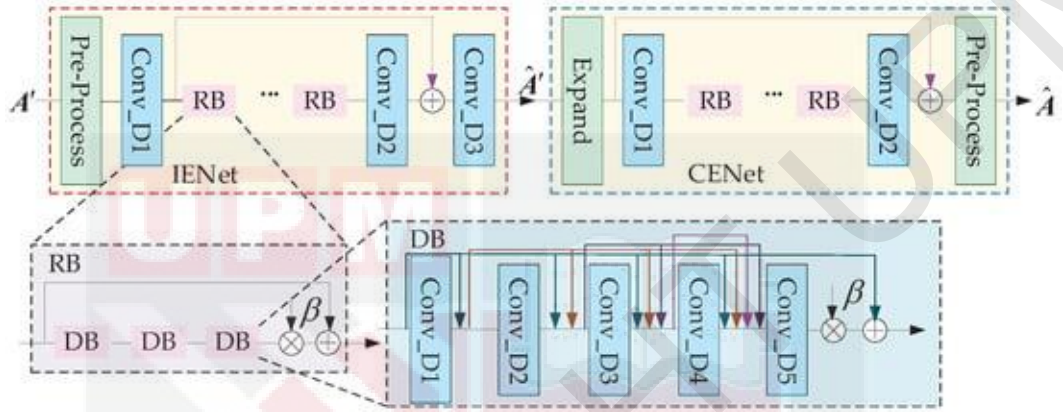


Figure 2.8: A deep learning architecture to estimate the channel in RIS systems[124]

5. **RNN:** Xu et al. [125] introduced a deep learning method that leverages partial channel data in the antenna domain to predict the full channel, which is crucial due to the high RIS element count and limited coherence time. To model temporal dependencies, they implemented a recurrent neural network (RNN). To handle the challenges of dynamic channels, [126] turned to deep reinforcement learning, proposing a solution based on deep deterministic policy gradients, which effectively mitigated interference from channels that vary with time. However, reinforcement learning algorithms used for RIS channel estimation experienced difficulties, particularly in defining data samples that represent state transitions, particularly those related to the RIS phase shift. In [127], a deep learning model was proposed, which utilized two deep neural networks to resolve this problem, demonstrating improved

performance when handling a significant number of RIS elements.

6. LSTM: In [128], the dual time-scale channel property was utilized by assuming that the channels between the base station (BS) and the RIS were static, while the channel between the RIS and the user was dynamic. The framework developed by Xu et al. [128] utilized long short-term memory (LSTM) networks to address the tasks of channel decomposition and prediction during the channel estimation phase. To enhance efficiency, they adjusted the connection layers to account for the nonlinear mapping between inputs and outputs. The various network architectures employed in RIS channel estimation, as discussed above, demonstrate the potential of deep learning techniques to improve performance. The framework proposed by Xu et al. [128] performed exceptionally well under difficult circumstances, such as environments with noisy, high-speed, and rapidly changing channels. Table 2.6 offers a summary of deep learning techniques for channel estimation and their results, analyzed based on antenna/RIS setup, channel model type, and the deep learning model's performance.

Table 2.6: A comparison of deep learning methods for RIS channel estimation

Ref.No.	Year	System Model	Channel Model	Algorithms
Xu et al. [125]	2022	MISO/Passive RIS	Time-varying Channel	Developed a two-stage network combining time interpolation and space extrapolation to enhance estimation accuracy.
Jin et al. [123]	2022	MIMO/Passive RIS	Static channel	Proposed GAN-CBD, CBDNet, and MRDNet to improve generalization and fitting capabilities.
Kundu et al. [129]	2021	MISO/Passive RIS	Static channel	Introduced a denoising CNN to decrease computational complexity and improve estimation accuracy.
Gao et al. [122]	2021	MIMO/Passive RIS	Static channel	Proposed a three-stage RNN training strategy to minimize pilot overhead and enhance estimation precision.
Ahmetm et al. [118]	2020	MIMO/Passive RIS	Static channel	Designed a CNN network to boost channel estimation accuracy.
Chen et al. [119]	2022	MIMO/Passive RIS	Static channel	Implemented a learning-based CNN to reduce computational complexity and improve channel estimation accuracy (eNMSE < 0.2 with more than 120 pilots).
Tekbiyik et al. [121]	2021	MIMO/Passive RIS	Static channel	Utilized a graph attention network to improve system robustness and decrease pilot overhead.
Liu et al. [120]	2022	MIMO/Passive RIS	Static channel	Developed deep residual and CNN networks to enhance estimation accuracy and reduce reflective elements by 70% compared to LMMSE (eNMSE = -8 dB).
Zhang et al. [124]	2021	MISO/Passive RIS	Static channel	Proposed a channel extrapolation network to improve estimation accuracy and network generalization.
Xu et al. [126]	2020	MIMO/Passive RIS	Time-varying Channel	Applied deep reinforcement learning to increase system capacity and suppress interference.
Li et al. [127]	2023	MIMO/Passive RIS	Static channel	Created a dual deep learning network to reduce computational complexity.
Xu et al. [128]	2022	MISO/Passive RIS	Time-varying Channel	Developed a sparse-connected LSTM network to improve estimation accuracy, reduce time delay, and decrease pilot overhead.

2.4.2 Channel Estimation for Different RIS Architectures

Channel estimation is considerably simpler in traditional active MIMO systems than in RIS-MIMO systems. This difference arises because active systems can directly acquire Channel State Information (CSI) using training sequences. In contrast, RIS systems, being passive, restrict estimation to the active transceivers. Additionally, the numerous Reconfigurable Elements (REs) in RIS significantly increase training overhead. Finally, the transmitter-RIS and RIS-receiver channel segments are inherently coupled with the RIS reflection matrix, making their estimation challenging. To overcome these estimation problems, research focuses on creating new methods to estimate the cascaded channel, which combines the transmitter-RIS and RIS-receiver links. We illustrate the importance of a standard multi-user MIMO system where a multi-antenna base station (BS) uses an RIS to serve multiple multi-antenna users to illustrate why estimating this cascaded channel is essential for optimizing both active (BS) and passive (RIS) beamforming. The channel paths from the BS to the RIS and from the RIS to the users are denoted by $H_{T,K,R}$, respectively. Then, the whole channel response from BS to UE is given by $H_{T,K} \text{diag}(\mathbf{v}) H_{K,R} = \mathbf{v}^T, \text{diag}(H_{K,R}) H_{T,K}$, where $\text{diag}(\mathbf{v})$ is the reflection coefficient matrix. Therefore, we know the joint design of active beamforming at the BS and passive reflection coefficient matrix $\text{diag}(\mathbf{v})$ at the RIS only requires the CSI of the following cascaded channel, i.e.,

$$H_k = \text{diag} (H_{K,R}) H_{T,K}, \quad (2.4)$$

H_k : This term typically denotes the overall channel matrix for a specific user or link in the system. It captures the combined effects of the transmission environment, including both direct and reflected paths. $\text{diag}(H_{K,R})$: The diag function indicates that $H_{K,R}$ is a diagonal matrix. This matrix may represent the channel gains or coefficients

from the RIS elements to the receiver. Each diagonal element corresponds to the gain associated with a particular path from the RIS to the user. $H_{T,K}$: This term represents the channel matrix from the transmitter to the RIS. It encapsulates how signals propagate from the base station (or transmitter) to the RIS, capturing factors such as distance, obstacles, and multipath effects. Consequently, the CSI of direct-link will not be addressed in this study since it is amenable to conventional estimation techniques inside the MIMO system. The main difficulty in channel estimation lies in determining the cascaded channel, which is a major area of focus in current research. The most advanced methods for cascaded channel estimation are generally grouped into two distinct categories: those that estimate the cascaded channel directly (cascaded channel estimation, CCE) and those that separate the estimation of the individual channels (separate channel estimation, SCE).

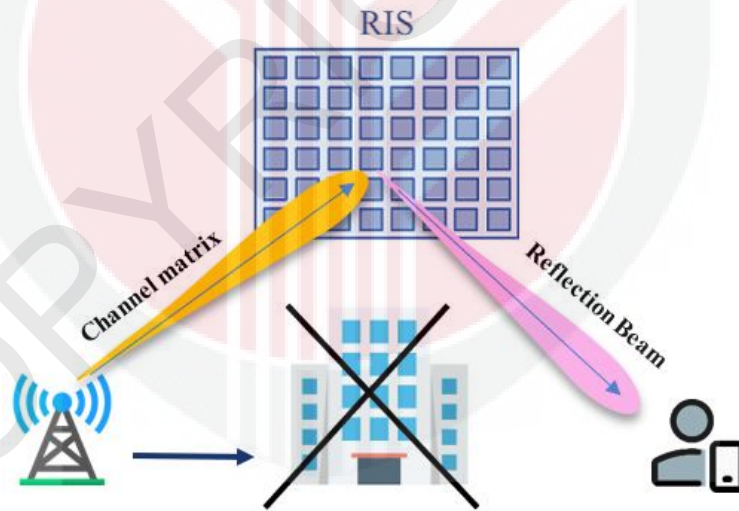


Figure 2.9: RIS-MIMO beamforming channel

2.4.2.1 Separate Channel Estimation Semi-Passive RIS

RIS systems can be categorized as either semi-passive or full-passive, depending on the presence of active sensors on the RIS. In this section, we discuss separate channel

estimation methods for each case. A semi-passive RIS, which integrates active sensors among its passive reflection elements (REs), provides one approach for estimating the RIS-related channel. The work in [130] is based on the premise that the BS-to-RIS and RIS-to-UE channels are composed of a small number of physical paths. Exploiting the inherent sparsity allows for full CSI recovery with minimal training signals. A limitation, however, is that the semi-passive RIS approach from [130] is restricted to correlated channel environments, and the integration of active sensors increases both hardware complexity and power consumption, as well as the complexity of signal processing. Additionally, the feedback link for CSI reduces transmission efficiency. Conversely, when a Reconfigurable Intelligent Surface (RIS) lacks active sensors, it's called a full-passive RIS. References [131, 132, 133, 134, 135, 136] explore distinct channel estimation methods for these full-passive RIS-MIMO systems. Specifically, [131, 132] examined RIS single-user MIMO systems. In reference [131], the BS-RIS channel was first determined using iterative solutions to a fixed-point equation. Subsequently, the RIS-User Equipment (UE) channel estimation utilized least squares (LS). To decrease training overhead, [132] leveraged the rank-deficient characteristics of the BS-RIS and RIS-UE channel matrices, employing a two-phase estimation approach. Initially, the matrix factorization problem was solved using the BiG-AMP algorithm, which recovered the BS-RIS channel and the combined RIS-UE channel/training pilot matrix. Subsequently, the matrix completion problem was tackled with a Riemannian manifold gradient-based algorithm to reconstruct the RIS-UE channel. Based on the assumption of sparse, low-rank, or quasi-static channels, SCE methods [133-136] were developed for channel estimation in RIS-aided multi-user MIMO systems. Reference [133], specifically, introduced a matrix-calibration-based factorization approach exploiting channel sparsity and used iterative Bayesian

inference to estimate BS-RIS and RIS-user channels independently. Separately, [134] proposed a two-phase, anchor-assisted strategy leveraging two nearby anchor nodes for enhanced estimation. In the initial phase of [134] approach, anchor nodes sequentially transmitted pilot signals to estimate the element-wise squared gain of the BS-RIS channel. This partial information was then used in the second phase to estimate the RIS-UE channels, facilitating efficient estimation in RIS-assisted massive access systems through information sharing among users. The approach in [135], by contrast, used parallel factor decomposition to express the high-dimensional tensor as a sum of rank-one tensors. The unknown channels were then reconstructed from these components using an alternating least squares (LS) algorithm.

2.4.2.2 Cascaded Channel Estimation Fully-Passive RIS

This subsection introduces the cascaded channel estimation (CCE) method, which directly estimates cascaded channels through a structured channel estimation protocol. A binary reflection technique, limiting activation to a single RIS element per pilot symbol, was proposed for an RIS single-user system in [137]. To estimate the direct BS-UE channel, an additional training symbol is required when all RIS elements are deactivated. However, implementing on/off switching for numerous RIS elements is costly and reduces accuracy since only a limited number of elements are active at a time. To overcome this, [138] proposed a sub-group-based binary reflection approach for RIS-based OFDM systems, leveraging spatial correlation. Instead of individually switching RIS elements, the method groups adjacent elements that share the same reflection coefficient, enhancing efficiency and estimation performance. The limitations of the binary reflection method, namely, high training overhead and weak

reflected signals, were addressed in [139] by proposing a full reflection-based CCE approach. This method, which keeps all reflecting elements (REs) active during the training timeslot, optimizes training reflection coefficients using the minimum variance unbiased estimation principle, resembling discrete Fourier transforms (DFT). Building on this, studies in [140, 141] integrated the full reflection approach with the grouping strategy from [138]. Furthermore, an alternative full reflection-based CCE method was proposed in [142, 143], utilizing a deep learning-based denoising convolutional neural network guided by the minimum mean-squared error (MMSE) criterion.

2.4.2.3 Combining Separate and Cascaded Channel Estimation Semi-Passive RIS

Both separate and cascaded channel estimation methods present distinct benefits and drawbacks. A preliminary comparison, as presented in [144], using atomic norm minimization, indicated that cascaded channel estimation provides improved estimation accuracy while reducing hardware expenses and energy usage. However, the impact of CSI errors and the cost-performance trade-offs in both methods are significantly affected by signal processing techniques, channel models, training designs, and hardware constraints. Consequently, a more thorough examination of these factors is crucial for future research. Currently, the separate and cascaded channel estimation methods are generally explored independently, which makes it an interesting avenue for future work to combine both approaches, leveraging their joint benefits to enhance channel estimation efficiency. As an illustration, the BS-RIS channel is usually high-dimensional, a consequence of the BS's multi-antenna setup, but remains nearly static because of the fixed locations of the BS and RIS. In contrast,

RIS-UE channels are more prone to change due to user mobility, but are lower-dimensional, since user devices have fewer antennas than the BS [145], [146], [147]. Given this, the quasi-static BS-RIS channel can be effectively estimated using the separate channel estimation approach, typically carried out by the sensing devices on the RIS. This hybrid channel estimation approach, conversely, uses existing knowledge of the quasi-static BS-RIS channel to estimate or track dynamic RIS-UE channels in real-time at the BS via cascaded estimation. This hybrid strategy could significantly reduce live training overhead compared to separate approaches and potentially increase usability for TDD and FDD systems.

2.4.3 Channel Estimation for Different RIS System Setups

Given the diverse system configurations and RIS deployments, such as single vs. multi-user, single vs. multi-RIS, varying numbers of antennas at the BS and UE, user mobility levels, and communication bandwidth, each scenario presents unique CSI requirements. To ensure efficient training and accurate estimation, tailored channel estimation strategies are necessary. This subsection delves into various RIS channel estimation approaches designed for different RIS setups, starting with single-RIS deployments and exploring their estimation techniques in both single-user and multi-user narrowband systems. Following that, we consider the emerging double- and multi-RIS systems, which introduce additional challenges due to the inter-RIS channels that further complicate the channel estimation process. For this study, we primarily focus on the single-RIS case and multi-user configurations.

2.4.3.1 Single-User System with Single RIS

For the single-user system with a single RIS, the effective channel is the combination of the direct channel and the reflected channels corresponding to a large number of RIS elements. Specifically, for the case of a single user where $K=1$ (and the user index k is omitted for simplicity), the cascaded channel can be expressed as: $\vec{H}=[\vec{h}_1, \vec{h}_2, \dots, \vec{h}_N]$, and thus the received signal at the BS with $K = 1$ can be expressed as [208]:

$$\mathbf{y}_B^{(t)} = \sqrt{P_u}((\mathbf{x}^{(t)})^T \otimes \mathbf{I}_{M_B})\vec{H} \boldsymbol{\theta}^{(t)} + \mathbf{v}_B^{(t)}, \quad (2.5)$$

The training overhead for resolving the full CSI of $\{\vec{h}_n\}_{n=1}^N$ is generally proportional to the number of $n=1$ reflecting elements N and thus may incur a long estimation delay. As such, how to effectively reduce the training overhead for the RIS-MIMO single-user system becomes a critical problem.

2.4.3.2 Multi-User System with Single RIS

Next, we consider the channel estimation for the RIS-MIMO multi-user system, where the received signal model is given in (2.6), and multiple users are served by a common RIS. It's crucial to understand that simply adapting channel estimation techniques designed for single-user systems to multi-user environments, such as through sequential user-by-user estimation, is not practically viable [148, 149]. In such situations, the received signal model from equation (2.5) simplifies to [208]:

$$\mathbf{y}_{B,k}^{(t)} = \sqrt{P_u}((\mathbf{x}^{(t)})^T \otimes \mathbf{I}_{M_B})\vec{H}_k \boldsymbol{\theta}^{(t)} + \mathbf{v}_B^{(t)}, \quad (2.6)$$

for all users k , ranging from 1 to K . In a way that is similar to the single-user scenario presented in (2.5), the combined CSI $\vec{H}_k$ each user's estimation is performed independently $y_{B,k}^{(t)}$ in Equation (2.6), if co-channel interference is ignored, training duration scales linearly with the user count. When the user count K is large, this scaling can become impractical. Therefore, enhancing training efficiency requires optimized designs for multi-user pilot sequences, RIS training reflection patterns, and a dedicated channel estimation algorithm suited for RIS-MIMO multi-user systems.

2.4.3.3 Double/Multi-RIS System

Previous studies on RIS channel estimation primarily addressed wireless systems supported by single or multiple distributed RISs, typically assuming only one signal reflection and often simplifying designs by omitting inter-RIS signal reflection. However, the potential of cooperative passive beamforming over the inter-RIS channel in double/multi-RIS MIMO systems has recently been acknowledged [150]–[151] and has revealed higher-order passive beamforming gains compared to a single-RIS setup. Despite the enhanced passive beamforming gain, the introduction of inter-RIS channels brings new challenges to channel estimation in double-/multi-RIS aided systems. As an example, considering a double-RIS-MIMO communication setup, a second RIS (RIS2) is positioned close to the base station, in addition to the standard RIS (RIS1) located near the users [150]. In this scenario, alongside the existing RIS1-BS and UE-RIS1 channels, denoted as G and H_k , respectively, we introduce $\tilde{G}$ and $\tilde{H}_k$ to represent the RIS2-BS and UE-RIS2 channels, respectively. Additionally, there is an inter-RIS channel between RIS1 and RIS2, denoted as S . Consequently, the

combined channel between the User Equipment (UE) and the Base Station (BS) is composed of the double-reflection path, the two single-reflection paths, and the direct path, as defined in [150]:

$$\mathbf{E}_k = \tilde{\mathbf{G}}\tilde{\boldsymbol{\Theta}}\mathbf{S}\boldsymbol{\Theta}\mathbf{H}_k + \tilde{\mathbf{G}}\tilde{\boldsymbol{\Theta}}\mathbf{H}_k + \mathbf{G}\boldsymbol{\Theta}\mathbf{H}_k + \mathbf{D}_k, \quad (2.7)$$

Where $\boldsymbol{\Theta} = \text{diag}(\theta)$ and $\tilde{\boldsymbol{\Theta}} = \text{diag}(\tilde{\theta})$ denote the diagonal reflection matrices of RIS1 and RIS2, respectively. Hence, as shown in (2.7), the RIS-MIMO links with different numbers of signal reflections are intricately coupled, resulting in a greater number of channel coefficients that need to be estimated. This complexity makes existing techniques for single-RIS channel estimation unsuitable for multi-RIS systems. We will now examine recent studies on channel estimation for double/multi-RIS-MIMO systems. However, accurately and efficiently determining the complete Channel State Information (CSI) for all single, double, and multi-reflection links in multi-RIS-MIMO systems with more than two cooperative RISs remains a challenge. This is largely due to the increased complexity caused by the growing number of interconnected channel coefficients, and this challenge remains an open problem for future investigation.

2.5 Deep Learning for Super-Resolution Channel Estimation in RIS-MIMO System

Channel estimation is crucial for improving RIS and Massive MIMO system performance. Traditional methods like LS and MMSE require extensive pilot signals, increasing overhead and reducing efficiency. In mmWave and THz systems, severe fading, multipath effects, and environmental noise further complicate estimation. Deep learning solutions are being examined by researchers to tackle these issues, leveraging

image super-resolution and denoising algorithms to enhance estimation accuracy. Super-resolution techniques, originally from image processing, reconstruct high-resolution signals from low-resolution data. In wireless systems, they refine coarse channel estimates from sparse pilot signals, improving resolution and accuracy. SRCNN, a widely used model, has proven effective in reducing pilot overhead while maintaining high estimation accuracy in RIS-MIMO systems. Various deep learning algorithms have also been developed to further enhance channel estimation performance.

Liu et al. [152] proposed a deep residual network and a convolutional neural network (CNN)-based architecture called CDRN to improve the channel estimation performance in RIS-MIMO multi-user systems. While CDRN shows promising results, it is important to note that its inputs are generated using the LS estimator, which is computationally intensive due to the high-dimensional cascaded channels.

Kundu et al. [153] used DnCNN and FFDNet CNN-based models for channel denoising in RIS-MIMO single-user MISO systems. They combined the LS channel matrix with a noise map representing the additive noise's standard deviation as input for FFDNet, enabling it to handle varying noise levels. However, this approach depends on the LS estimator and faces challenges since real-world applications often lack additive noise information.

To improve the use of compressive sensing for channel estimation within RIS-MIMO millimeter-wave massive MIMO systems, Gao et al. [154] developed a complex-valued denoising convolutional neural network (CV-DnCNN). Jin et al. [155] suggested EDSR and MDSR residual networks for reconstructing the channel matrix

from sparse RIS channels in TDD RIS-MIMO mmWave systems. Their hybrid RIS structure includes active elements connected to a baseband unit for signal processing. Channel estimation is performed at the receiver, generating inputs for CV-DnCNN, EDSR, and MDSR models. Integrating super-resolution and denoising techniques enhances estimation accuracy and improves the signal-to-noise ratio (SNR).

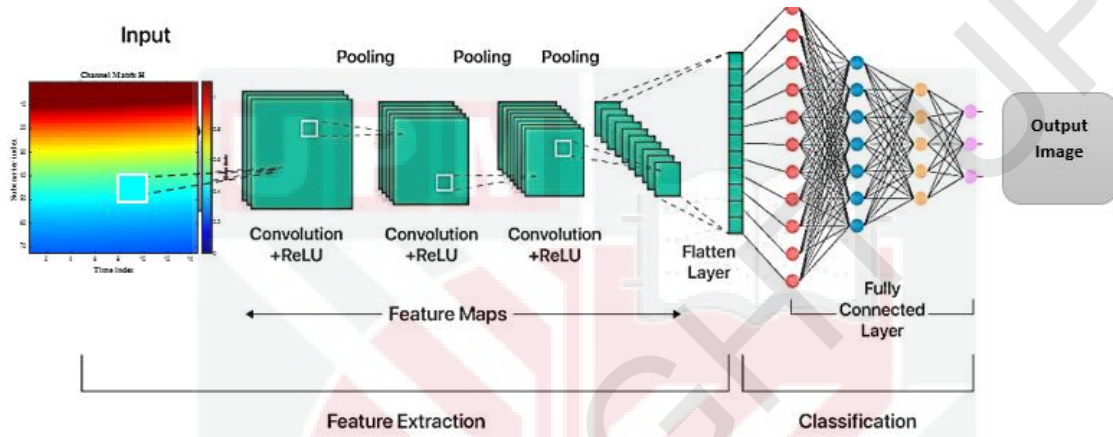


Figure 2.10: CNN Architecture for Channel Estimation

Figure 2.10 shows the structure of a CNN designed specifically for channel estimation tasks. It includes a 2D input layer: the input layer receives the channel state information, represented as a 2D image (time-frequency grid). Convolutional layers: These layers automatically extract relevant features from the input data, capturing spatial correlations and patterns critical for accurate channel estimation. Output layer: The final layer produces estimates of the channel conditions, enhancing the overall performance compared to traditional estimation methods.

We chose Convolutional Neural Networks (CNNs) because we represent the channel time-frequency response as a 2D image. CNNs are well-suited for image data, as they can effectively extract spatial features and patterns through their convolutional layers,

which makes them ideal for processing 2D images. By transforming the channel data into a 2D image, CNNs can capture the inherent correlations within the data, improving the accuracy of channel estimation in RIS-MIMO systems. This approach takes advantage of the well-established capabilities of CNNs in image processing, making them a powerful tool for handling complex, high-dimensional data in communication systems.

2.6 Dataset Generation

The Vienna 5G Simulator is a powerful tool-based MATLAB designed to simulate the performance of 5G communication systems at the link and system level. Developed by the Institute of Telecommunications at TU Wien (Vienna University of Technology), this simulator evolves earlier LTE and LTE-A simulators and is specifically tailored to the unique requirements of 5G networks. The simulator provides a comprehensive framework for evaluating various aspects of 5G physical-layer technologies and their impact on link and system-level performance.

2.6.1 5G Link Level Simulator

The Vienna 5G Link Level Simulator is an open source software tool used to evaluate the performance of 5G communication systems at the link level. It provides an extensive framework for simulating various aspects of 5G networks, focusing on physical layer functionalities. The Vienna 5G Link Level Simulator has been extensively utilized in recent research to enhance channel estimation techniques, particularly in the context of Reconfigurable Intelligent Surfaces (RIS) and advanced

wireless communication systems. In a significant contribution, Qian et al. [156] detailed an anchor-aided method for channel estimation in RIS-MIMO multiuser broadband systems. This approach leverages anchor points to improve the accuracy of channel estimates, demonstrating the simulator's capability to model complex scenarios effectively. A new approach to channel parameter estimation, utilizing SAGE, was proposed by Xu et al. [157] for 6G RIS-MIMO wireless communication. The authors utilize the Vienna simulator to validate their proposed method, showcasing its effectiveness in accurately estimating channel parameters under various conditions. This study highlights the simulator's role in facilitating research on next-generation communication technologies. A. Demaj et al. [158] focus on the verification of both link-level and system-level simulators, emphasizing the importance of accurate simulation results in developing reliable channel estimation techniques. Their work illustrates how the Vienna 5G Link Level Simulator can be integrated with system-level simulations to provide comprehensive insights into channel behavior and performance metrics. In addition, Zhang and Jiang [159] explore over-the-air phase calibration techniques for RIS, utilizing the Vienna simulator to assess the impact of phase calibration on channel estimation accuracy. Their findings contribute to understanding how phase adjustments can optimize signal quality and enhance overall system performance. A framework named TRICE for channel estimation in RIS-assisted millimeter-wave MIMO systems is presented by Ardah et al. [160]. Their research demonstrates how the Vienna simulator can be employed to evaluate the effectiveness of their proposed framework in real-world scenarios, further validating the simulator's utility in advancing channel estimation methodologies. Using the Vienna simulator, Mao et al. [161] examined channel estimation techniques for RIS-MIMO wireless communication systems in mobile environments. Their study

provides insights into how mobility affects channel characteristics and emphasizes the need for robust estimation techniques that can adapt to dynamic environments. Cai et al. [162] discuss downlink channel tracking for intelligent reflecting surface-aided FDD MIMO systems, utilizing the Vienna simulator to analyze various tracking algorithms' performance. Their findings underscore the importance of accurate channel tracking in maintaining high data rates and reliable connections. These studies collectively demonstrate the significant role of the Vienna 5G Link Level Simulator in advancing research on channel estimation techniques, providing researchers with a robust platform for exploring new methodologies and validating their effectiveness in complex communication environments.

Table 2.7: Recent studies that utilize the Vienna 5G Link Level Simulator for advancing channel estimation methodologies in wireless communication systems

No.	Author	Year	Communication System	Channel Model	Performance Analysis Improved
[156]	Qian et al.	2023	RIS-assisted multiuser broadband	Anchor-aided channel model	Improved accuracy of channel estimation using anchor points.
[157]	Xu et al.	2022	5G RIS-assisted wireless channels	SAGE-based channel parameter estimation	Enhanced parameter estimation accuracy under various conditions.
[158]	Ademaj et al.	2022	Vienna 5G Link and System Level Simulators	Link performance models	Validated interaction between link-level and system-level simulators for improved results.
[159]	Zhang & Jiang	2023	Reconfigurable Intelligent Surfaces (RIS)	Phase calibration model	Optimized phase calibration techniques for better channel estimation accuracy.
[160]	Ardah et al.	2021	RIS-aided millimeter-wave MIMO	TRICE framework for channel estimation	Evaluated the effectiveness of the TRICE framework in real-world scenarios.
[161]	Mao et al.	2021	RIS-assisted wireless communication	Mobility-affected channel model	Addressed mobility effects on channel characteristics for robust estimation techniques.
[162]	Cai et al.	2021	Intelligent Reflecting Surface-aided FDD MIMO	Downlink channel tracking model	Analyzed the performance of tracking algorithms to maintain high data rates.
[163]	Koutlia et al.	2023	5G-LENA system-level simulator	Calibration in 3GPP reference scenarios	Ensured simulation relevance and accuracy for evaluating new technologies.

Key Features and Capabilities:

- i. **Physical Layer Simulation:** Supports a wide range of functionalities, including channel estimation, modulation, coding, and MIMO techniques, allowing comprehensive performance assessments under various conditions.
- ii. **Channel Modeling:** Features sophisticated models to simulate real-world environments, accounting for impairments such as noise, interference, and multipath propagation.
- iii. **Modular Design:** It offers a modular architecture for easy integration and testing of new algorithms and techniques, making it suitable for diverse research and development tasks.
- iv. **Configuration and Customization:** Users can configure parameters like transmission power, bandwidth, and modulation schemes to study their impact on system performance, enabling detailed evaluations.
- v. **Performance Metrics:** Provides various metrics, including signal-to-noise ratio (SNR), bit error rate (BER), and throughput, essential for analyzing the efficiency and reliability of 5G systems.
- vi. **Integration with Other Tools:** It can be integrated with other simulation tools and frameworks to enhance functionality and enable complex system analyses.
- vii. **User-Friendly Interface:** Features a graphical interface and extensive documentation, making it accessible for both novice and experienced users for rapid deployment and testing.
- viii. **Research and Development:** Widely used in academia and industry to explore new ideas, test hypotheses, and validate 5G technologies. Its open-source nature fosters collaboration and continuous improvement within the research community.

The Vienna 5G Link Level Simulator has become a pivotal tool for advancing 5G technology, providing valuable insights into the performance and optimization of 5G networks. Its comprehensive features and flexibility make it an essential resource for researchers and engineers working in the field of wireless communication [24].

The representation of signals in the time-frequency domain is essential for analyzing and processing complex data in various fields, including communications, audio

processing, and biomedical engineering. In particular, color representation in time-frequency images allows for a visual interpretation of how signal energy is distributed over time and frequency, which is crucial for applications such as channel estimation in RIS-MIMO systems. This literature review explores the methodologies and implications of using normalized real/imaginary 2D images in time-frequency grids. Time-frequency analysis techniques, such as the Short-Time Fourier Transform (STFT) and Wavelet Transform, enable the decomposition of signals into their constituent frequency components over time. These methods produce time-frequency representations that can be visualized as 2D images:

- i. **STFT:** This technique involves segmenting the signal into overlapping windows and applying the Fourier transform to each segment. The resulting spectrogram provides a visual representation where time is on one x-axis and frequency on the other, with color intensity indicating amplitude [164].
- ii. **Wavelet Transform:** Unlike STFT, wavelet transform offers better localization in both time and frequency domains, making it suitable for analyzing non-stationary signals. The resulting scalograms can also be represented as 2D images [165].

Using normalized real and imaginary components to create 2D images for channel time-frequency grids offers several key advantages [166]. First, it enhances interpretability by allowing researchers to analyze phase and amplitude information separately, resulting in a more comprehensive understanding of signal behavior. Second, it improves model training in machine learning applications, particularly with CNNs, as normalized inputs help stabilize the training process by ensuring consistent data distributions across different features [165]. Lastly, it facilitates the handling of complex-valued data, thanks to recent advancements in deep learning frameworks. For instance, MATLAB's image input layer now supports complex inputs, enabling

effective processing without requiring the separation of real and imaginary components [164].

The color representation in a 2D image time-frequency response is crucial for interpreting the characteristics of signals in RIS-MIMO channels. This representation allows us to visualize how signal energy is distributed across different frequencies over time, facilitating analysis and processing in machine learning applications, particularly with Convolutional Neural Networks (CNNs)[167].

Color Mapping: In OFDM signal visualization, different colors are employed to represent the amplitude or power level of various frequency components at specific times. This visualization technique is crucial for understanding the signal's behavior across the channel bandwidth graphically and intuitively:

- i. **Red and Orange:** These colors signify higher amplitudes or energy levels in specific subcarriers at given time intervals. Typically, these colors indicate stronger channel responses or higher signal power.
- ii. **Yellow and Green:** These hues are used to denote medium magnitudes, which correspond to moderate signal strengths within the channel. This range often represents a typical response where the signal is neither too strong nor too weak, ensuring reliable transmission without excessive power consumption.
- iii. **Blue and Dark Blue:** Cooler colors, such as blue, are indicative of lower magnitudes. These colors represent weaker channel responses or reduced signal power, which may result from factors such as signal fading, path loss, or destructive interference.

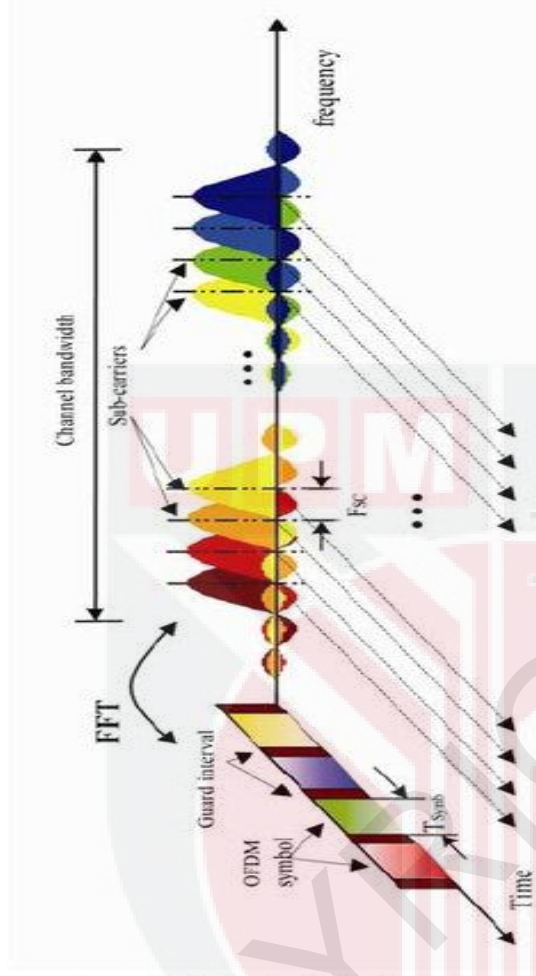
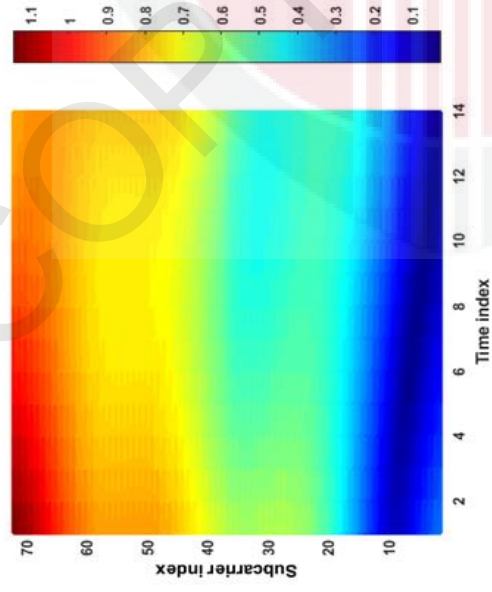


Figure 2.11: An illustration of a normalized real/imaginary 2D image for a channel time-frequency grid [168][169]

Table 2.8: Color Mapping of OFDM Signal Components

Color	Magnitude Range	Frequency Range (Hz)	Description
Red and Orange	High	2.5 GHz - 3.0 GHz	Signify higher amplitudes or energy levels, indicating stronger channel responses or higher signal power.
Yellow and Green	Medium	2.0 GHz - 2.5 GHz	Denote medium magnitudes, representing moderate signal strengths in the channel.
Blue and Dark Blue	Low	1.5 GHz - 2.0 GHz	Indicate lower magnitudes, corresponding to weaker channel responses or reduced signal power due to factors like fading, path loss, or destructive interference.

The 2D image is structured with the x-axis representing time and the y-axis representing frequency, allowing for a clear visualization of how signal characteristics change over time and how various frequency components contribute to the overall signal. This layout is particularly useful for analyzing dynamic behaviors in communication systems. Additionally, the Fourier Transform decomposes the signal into its constituent frequencies, providing complex numbers that carry both magnitude and phase information. For effective visualization, the magnitude represents the strength of each frequency component, while the phase indicates its relative position in the signal.

- i. **The magnitude:** (often represented by color intensity) indicates the strength of each frequency component.
- ii. **The phase:** While important for signal reconstruction, it is typically not visualized directly but can influence how we interpret the overall structure of the time-frequency image.

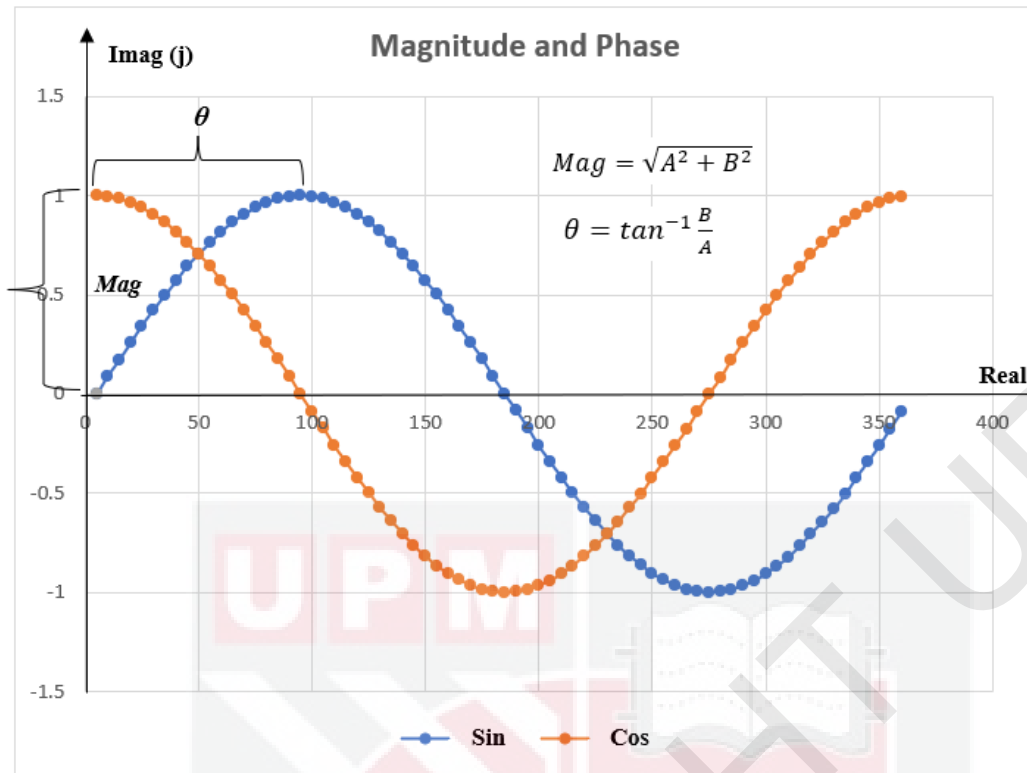


Figure 2.12: Complex Signal Representation with Magnitude and Phase Components

The scale on the right side of the 2D image typically indicates the magnitude or intensity of the signal at various points in the time-frequency plane. This scale can represent different metrics, such as power or amplitude, and is often color-coded to enhance visual interpretation. The magnitude is measured in a linear scale (unitless), representing the absolute values of the channel coefficients. For instance, darker colors may signify higher magnitudes, while brighter colors indicate lower magnitudes. By analyzing the color-coded time-frequency image, key signal features can be identified, such as areas of high energy concentration that highlight dominant frequencies essential for communication and transitions or abrupt color changes that indicate modulation or variations in signal properties over time [165].

In RIS-MIMO systems, the time-frequency representation provides valuable insights into signal propagation through the channel. It helps observe the effects of multipath propagation and reflections from RIS elements, which appear as variations in frequency content over time. This representation is critical for assessing channel conditions, such as fading and interference patterns. Additionally, these 2D images are highly useful for machine learning applications, particularly for CNNs. When used as input data, CNNs can learn to recognize patterns associated with different channel conditions or signal types. Training on these images enhances classification and detection capabilities, improving the performance of RIS-MIMO systems. Accurate channel estimation is crucial in RIS-MIMO systems to optimize overall performance. The use of color-coded, normalized 2D images facilitates several key tasks, including channel characterization, by visualizing how signals propagate through environments influenced by RIS elements. In wireless communications, understanding time-frequency behavior aids in optimizing transmission strategies and reducing pilot overhead. Moreover, CNNs trained on these representations can effectively classify different channel states or detect anomalies, thereby improving communication reliability and robustness.

The integration of color representation in normalized real/imaginary 2D images for time-frequency grids represents a significant advancement in signal analysis techniques. By leveraging these methodologies, researchers can gain deeper insights into signal characteristics and improve model performance in RIS-MIMO systems.

The design and optimization of pilot patterns are crucial for accurate channel estimation in modern wireless communication systems, particularly in Orthogonal

Frequency Division Multiplexing (OFDM) and RIS-MIMO systems. Among various pilot structures, the diamond pilot pattern has attracted attention due to its unique geometrical arrangement, which offers several benefits in terms of estimation accuracy, overhead reduction, and robustness to interference. The pilot design described here refers to the settings for pilot patterns, namely the Diamond patterns, and defines how the pilot symbols are spaced in both the frequency and time domains.

- i. Pilot Spacing in Frequency Domain (pilot Spacing Frequency = 6): This parameter defines the spacing of pilot symbols in the frequency domain, which can be fractional (such as 6 subcarriers apart). It indicates how frequently pilot symbols are placed in the frequency spectrum.
- ii. Pilot Spacing in Time Domain (pilot Spacing Time = 3.5): This defines the spacing of pilot symbols in the time domain, with fractional values allowed (such as 3.5 symbols apart). This setting governs the distribution of pilot symbols over time.
- iii. Pilot Sequence Length (pilot sequence length = 12): This is the length of the orthogonal pilot sequence used for channel estimation. In the context of Multi-User MIMO, this length defines the maximum number of users that can be supported by the channel estimation process. Each user is assigned a unique sequence for better separation and estimation.

Figure 2.13 illustrates two dynamic pilot patterns used across subcarriers and symbols in OFDM systems. The diamond pilot pattern inserts pilots across both time and frequency domains, allowing for more accurate channel estimation by capturing variations in both dimensions. In contrast, the block pilot pattern places pilots only in the frequency domain, which limits its ability to track time-domain variations accurately. These patterns are designed to optimize pilot allocation, facilitating accurate channel estimation while maintaining spectral efficiency.

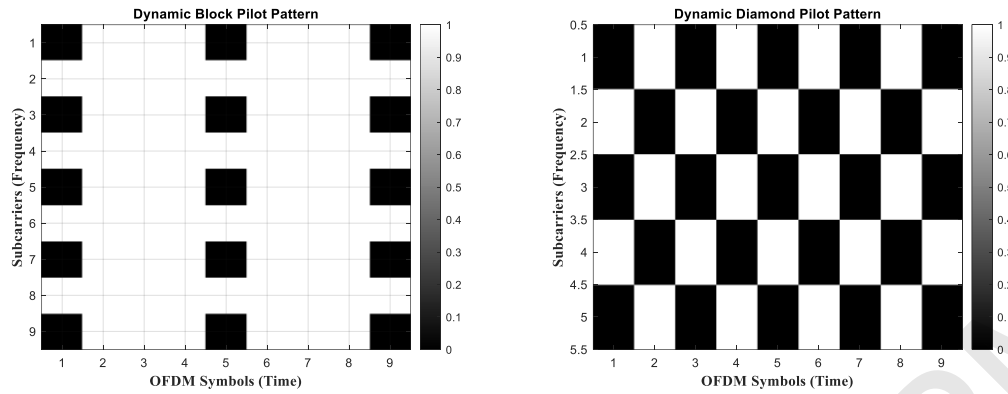


Figure 2.13: The dynamic Block and diamond pilot pattern across subcarriers and Symbols

These settings influence the overall pilot pattern design, determining how pilot symbols are distributed across the time-frequency grid for effective channel estimation in systems such as MIMO. The pilot spacing ensures that pilots are spread efficiently, balancing between the need for accurate channel estimation and the available time-frequency resources.

2.6.2 5G System Level Simulator

The Vienna 5G System Level Simulator is another significant tool developed by the Institute of Telecommunications at the Vienna University of Technology, designed for evaluating and optimizing the performance of 5G communication systems, but at a system level rather than the link level. While the Vienna 5G Link Level Simulator focuses on the physical layer, the System Level Simulator addresses broader aspects of network performance and behavior. Below is an overview of key features and capabilities commonly found in 5G system-level simulators.

Key Features and Capabilities:

- i. **System-Level Simulation:** Models entire 5G networks, including multiple base stations (gNodeBs) and user equipment (UE), allowing assessment of network-wide performance metrics and interactions.
- ii. **Network Topology and Traffic Models:** Supports detailed modeling of network topology and various traffic models to simulate real-world usage patterns, helping evaluate the impact of different designs and conditions on system performance.
- iii. **Advanced Features and Protocols:** Simulates advanced 5G features and protocols like network slicing, ultra-reliable low-latency communication (URLLC), and massive MIMO, enabling researchers to study their effects on performance and user experience.
- iv. **Performance Metrics:** Provides a range of metrics relevant to system-level analysis, such as network throughput, user experience, latency, and coverage, crucial for understanding different network configurations.
- v. **Integration with Link Level Simulation:** This can be integrated with the Vienna 5G Link Level Simulator for comprehensive analysis, evaluating physical layer performance alongside system-level factors.
- vi. **Scalability and Flexibility:** Designed for large-scale simulations, suitable for networks with many base stations and users, with a flexible architecture for customization to various research needs.
- vii. **User-Friendly Interface and Documentation:** Offers a graphical interface and extensive documentation for ease of use by researchers and engineers, facilitating efficient simulation configuration and result analysis.
- viii. **Open-Source and Research Community:** As an open-source tool from the Vienna University of Technology, it promotes collaboration and continuous development within the research community, encouraging innovation in 5G network design.

The Vienna 5G System Level Simulator is a powerful tool for evaluating the performance and optimization of 5G networks from a system-wide perspective. Its comprehensive features and flexibility make it an invaluable resource for researchers and engineers working on the development and deployment of 5G technologies [24].

2.7 Performance Metrics

Reconfigurable Intelligent Surfaces (RIS) have emerged as a transformative technology in 5G and beyond, enhancing wireless communication systems' performance. This literature review examines key performance metrics relevant to RIS-MIMO systems, including Data Rate, Normalized Mean Square Error (NMSE) and Mean Square Error (MSE), Channel Gain, Path Loss, Accuracy, Capacity, Bit Error Rate (BER), and Throughput. Each metric is critical for evaluating the effectiveness of RIS-MIMO communication systems.

2.7.1 Data Rate

The data rate is a fundamental performance metric that quantifies the information transmitted over a channel in a given time frame. In RIS-MIMO systems, the data rate can be influenced by various factors, including channel conditions and the number of antennas. The achievable data rate R can be expressed as:

$$R = B \log_2(1 + SNR) \quad (2.8)$$

Where B is the bandwidth and SNR is the signal-to-noise ratio. Recent studies have shown that RIS can significantly enhance data rates by improving signal quality through better channel estimation and interference mitigation [170,171].

2.7.2 Normalized Mean Square Error (NMSE) and Mean Square Error (MSE)

NMSE and MSE are crucial for assessing channel estimation accuracy in RIS-MIMO systems.

$$MSE = \frac{1}{N} \sum_{i=1}^N (x_i - \hat{x}_i)^2 \quad (2.9)$$

where x_i represents the actual values and $\hat{x}_i$ are the estimated values.

$$NMSE = \frac{MSE}{\sigma^2} \quad (2.10)$$

where σ^2 is the variance of the actual signal. These metrics are essential for evaluating the performance of channel estimation algorithms in RIS-MIMO systems, where accurate channel information is critical for optimizing transmission strategies [170,173].

2.7.3 Channel Gain

Channel gain quantifies how much the signal power increases as it propagates through a communication channel. It is influenced by distance, obstacles, and environmental conditions [171,172].

Higher channel gains lead to improved signal quality and higher data rates. Accurate estimation of channel gain is vital for effective resource allocation in RIS-MIMO systems.

2.7.4 Path Loss

Path loss refers to the reduction in signal strength as it travels from the transmitter to the receiver. It significantly impacts communication quality in wireless networks. Common models include Free Space Path Loss and empirical models like Hata or COST-231, which account for urban environments. A basic path loss model can be expressed as:

$$PL(d) = PL_0 + 10n \log_{10}\left(\frac{d}{d_0}\right) \quad (2.11)$$

Where PL_0 is the path loss at a reference distance d_0 , n is the path loss exponent, and d is the distance between the transmitter and the receiver. Understanding path loss characteristics is crucial for designing effective coverage strategies in RIS-MIMO networks [171,172].

2.7.5 Capacity

Capacity refers to the maximum data rate a communication channel can support under specific conditions. The Shannon Capacity Equation:

$$C = B \log_2(1 + SNR) \quad (2.12)$$

This equation illustrates how capacity increases with bandwidth and SNR, emphasizing the importance of optimizing these parameters in RIS-MIMO systems [170,171].

2.7.6 Bit Error Rate (BER)

BER measures the number of bit errors divided by the total number of transferred bits during a specified time interval. It serves as an indicator of transmission quality. The BER can be expressed as:

$$BER = \frac{N_e}{N_t} \quad (2.13)$$

Where N_e is the number of erroneous bits and N_t is the total number of bits transmitted. Low BER values indicate reliable communication, which is essential for applications requiring high data integrity [170,171].

2.7.7 Throughput

Throughput refers to the actual data transfer rate achieved over a network and is often lower than the theoretical maximum due to various factors such as network congestion and protocol overhead. The Throughput can be calculated as:

$$T = R - L \quad (2.14)$$

Where R is the data rate and L represents any overhead or lost packets during transmission. Understanding throughput helps in assessing real-world network performance, particularly in dense environments where RIS technology is deployed [172,173].

The evaluation of performance metrics such as Data Rate, NMSE/MSE, Channel Gain, Path Loss, Accuracy, Capacity, BER, and Throughput is essential for optimizing RIS-MIMO systems. These metrics provide insights into network efficiency, reliability, and user satisfaction, guiding engineers in designing robust communication networks capable of meeting modern demands.

2.8 Related Works

This section reviews the existing literature on channel estimation techniques pertinent to RIS-MIMO systems. This discussion is divided into two subsections: focusing on channel estimation-related resolution challenges and addressing channel estimation for phase shift and beamforming control.

2.8.1 Related Work on Channel Estimation for SRIR-CNN Algorithm

The recent evolution of deep learning has substantially altered channel estimation techniques in wireless communication systems, primarily by leveraging Super-Resolution Convolutional Neural Networks (SRCNN) and Denoising Convolutional Neural Networks (DnCNN).

Liu et al. [174] This paper introduces a deep residual learning framework tailored for channel estimation in RIS-MIMO multi-user communications. The authors demonstrate that their approach, which incorporates DnCNN, effectively enhances channel estimation accuracy by leveraging the residual connections to mitigate information loss during training. The results show significant improvements in

normalized mean square error (NMSE) compared to traditional methods. Shen et al. [175] in this study, the authors propose a novel SRCNN-based approach for super-resolution channel estimation specifically designed for RIS-MIMO systems. They highlight the effectiveness of SRCNN in reconstructing high-resolution channel frequency responses from low-resolution estimates, achieving better performance metrics such as BER and throughput in various scenarios. Zhang et al. [176] this paper present NDR-Net, which integrates DnCNN within its architecture to estimate channels under varying noise conditions. The model first estimates noise levels and then applies DnCNN to enhance the channel estimates. The results indicate that NDR-Net outperforms traditional channel estimation techniques, particularly in dynamic environments with unknown noise levels. Kim et al. [177] this paper evaluate various machine learning approaches, including DnCNN, for estimating channel frequency responses in ATSC 3.0 systems. The authors find that while DnCNN improves performance over conventional methods, it faces limitations when applied to nonlinear channels, highlighting the need for further research into hybrid models that combine multiple techniques. Ginige et al. [178] this comprehensive review discusses various deep learning architectures used for channel estimation, emphasizing the roles of SRCNN and DnCNN. The authors analyze performance metrics across different applications, including RIS-MIMO systems, and provide insights into challenges and future directions for integrating these models into practical scenarios. Chen et al. [179] this study focuses on utilizing DnCNN to enhance channel estimation in Orthogonal Frequency Division Multiplexing (OFDM) systems. The authors propose a framework where DnCNN is employed to denoise initial channel estimates obtained through conventional methods, resulting in improved accuracy and robustness against noise. Wang et al. [180] in this paper, the authors explore super-resolution techniques based

on SRCNN to enhance channel estimation in MIMO systems. They demonstrate that their approach effectively reconstructs high-resolution channel matrices from low-resolution observations, leading to better system performance metrics such as capacity and reliability. This comparative study, by Zhao et al. [181], provides an evaluation of diverse deep learning models, such as FSRCNN and DnCNN, concerning channel estimation in RIS-MIMO communications. The authors conduct extensive simulations to assess the performance of each model under different conditions, concluding that while both models show promise, SRCNN offers superior results in scenarios requiring high-resolution estimates. Muneeb et al. [182] this paper propose a novel image-based deep learning approach for channel estimation that leverages super-resolution techniques. The authors utilize SRCNN to enhance low-quality channel estimates by treating them as images, significantly improving the accuracy of channel predictions and symbol detection compared to conventional estimators. In their work, Haq et al. [183] present ChannelNet, a method that frames channel estimation as an image reconstruction task and employs SRCNN and DnCNN to transform low-resolution, noisy channel estimates into high-resolution images, showcasing significant improvements in channel estimation accuracy while maintaining low computational complexity.

Table 2.9: Comparison of Deep learning-based algorithms to improve Channel Estimation Accuracy

Ref.	Year	Antenna/RIS Architecture	Problem	Major Algorithm	Performance Analysis Improved
[182]	(Muneeb et al., 2023)	MIMO-NOMA	Resolution and noise problems	SRDnN-CNN	Improved estimation accuracy
[184]	(Soltani et al., 2020)	OFDM-MIMO	Resolution and noise problem	ConcreteAE-MLP	Improved estimation accuracy, reduced time delay
[185]	(Kundu & McKay, 2021) IEEE	MISO/Passive RIS	Resolution and noise problems	Denoising and FFDNet	Reduced computational complexity and improved estimation accuracy
[186]	(Nithya & Brijesh, 2023) IEEE	MIMO/Passive RIS	Resolution and noise problem	FFDNet	reduce the total number of operations without compromising performance
[187]	(Wang et al., 2023)	MINE-OFDM	Resolution and noise problems	EDSR	Improved estimation accuracy
[188]	(Yazheng & Wang 2021)IEEE	RIS-millimeter wave	Resolution problems	SRCNN	To reduce the overhead and obtain accurate CSI,

2.8.2 Related Work on Channel Estimation for Cascaded and Separate Channels

The period from 2019 to the present has seen notable progress in Reconfigurable Intelligent Surface-MIMO systems. Research has predominantly focused on two key areas: phase shift optimization and data rate prediction, with specific methodologies tailored to both cascaded and separate channel configurations. There are two types of CSI: the separate channels for the $S \rightarrow \text{RIS}$ and $\text{RIS} \rightarrow D$ links and the cascaded channels for the end-to-end $S \rightarrow \text{RIS} \rightarrow D$ links, respectively.

For cascaded channels, Sheen et al. [189] this paper present a deep-learning approach that models the interactions between the phase shifts of RIS elements and receiver locations. The authors propose a method to predict achievable rates directly without relying on channel state information (CSI) or pilot signals, thus addressing the pilot overhead issue. Chung et al. [190] in this study, a comprehensive review discuss various channel estimation techniques in RIS-MIMO systems. It emphasizes the challenges of high training overhead and proposes deep learning-assisted methods that reduce pilot requirements while improving estimation accuracy through enhanced spatial and temporal sampling. Zhang et al.[191] this study introduces a deep learning framework specifically designed for cascaded channel estimation in RIS-MIMO systems. The authors utilize a dual-stage neural network that effectively reduces pilot overhead while accurately estimating the cascaded channels by leveraging the spatial correlation of users. Xu et al.[192] this paper addresses the issue of pilot overhead by proposing an efficient pilot design strategy that minimizes training symbols while maintaining high estimation accuracy. The authors incorporate a deep learning model to optimize pilot allocation based on user distribution and channel conditions. Li et

al.[193] this research explores the use of Generative Adversarial Networks (GANs) for cascaded channel estimation in RIS-MIMO systems. The authors demonstrate that their GAN-based approach can effectively reconstruct high-resolution channel estimates from low-resolution data while reducing pilot overhead. Kundu et al.[194] this study focuses on optimizing phase shifts at RIS using deep learning techniques. The authors propose a neural network model that learns from received pilot signals to dynamically adjust phase configurations, thereby enhancing signal quality and reducing training overhead. Peng et al.[195] this paper presents a novel pilot-aided channel estimation method that employs deep learning to enhance performance in RIS-MIMO systems. The authors show that their approach significantly reduces the number of required pilots while achieving comparable or better NMSE performance than conventional methods. Wu et al.[196] this research introduces adaptive channel estimation techniques that utilize deep learning models to adjust dynamically to varying channel conditions in RIS-MIMO systems. The authors demonstrate how their method reduces both phase shift configuration complexity and pilot overhead through intelligent adaptation.

For separate channel scenarios, Zhang et al. [197] this paper propose a two-stage channel estimation protocol that leverages semi-passive elements to reduce pilot overhead. The authors introduce an iterative re-weighting-based super-resolution algorithm for estimating the BS-RIS channel and a parallel factor decomposition method for the UE-RIS channel, demonstrating improved accuracy and reduced pilot requirements. Kolliboina et al. [198] this review discusses various deep learning methods applied to channel estimation in RIS-assisted systems, highlighting the challenges of pilot overhead and phase shift optimization. The paper categorizes

existing techniques and provides insights into future research directions in semi-passive RIS configurations. Following that, Taha, A. et al. [199], the authors discuss the integration of compressive sensing with deep learning to enhance the performance of large intelligent surfaces (LIS). The authors propose a framework that reduces pilot overhead and improves channel estimation accuracy by leveraging sparsity in the channel matrix and employing deep neural networks for reconstruction. Alrabeiah et al. [200] this foundational work sets the stage for utilizing deep learning in RIS configurations. The authors explore how deep learning can optimize channel estimation processes in massive MIMO systems, addressing pilot overhead challenges effectively. Taha, A., et al. [201] this paper explores the application of deep reinforcement learning to optimize the operation of intelligent reflecting surfaces, focusing on phase shift adjustments and pilot signal management. The proposed approach demonstrates significant improvements in channel estimation accuracy while reducing pilot overhead through adaptive learning strategies. Jin, Yu, et al. [202] in this study first integrate an RIS with a small number of uniformly distributed active sensing devices, which are equipped with active radio frequency chains for acquiring partial channel state information (CSI). Subsequently, capitalizing on the rank-deficient nature of RIS channels, two viable residual neural network architectures, specifically single-scale enhanced deep residual (EDSR) and multi-scale enhanced deep residual (MDSR), are presented to acquire precise Channel State Information (CSI). Mirza A. et al. [203] in this approach efficiently enables channel estimation both between the base station and the RIS, as well as between the RIS and the mobile users. Structured covariance matrix interpolation optimally utilizes the array aperture from the sparsely placed active RIS elements.

Table 2.10: A comparison of deep learning algorithms for RIS channel estimation

Ref.	Year	Antenna/RIS Architecture	Major Problem	Major Algorithm	Performance Analysis Improved
[189]	2024	MIMO/Passive RIS	Pilot overhead	Deep Learning for Phase Shift Prediction	Predicts achievable rates without CSI or pilot signals, reducing pilot overhead.
[190]	2023	MIMO/Passive RIS	training overhead	Deep Learning Techniques (CNN, RNN)	Reduces training overhead and improves estimation accuracy through enhanced sampling.
[191]	2023	MIMO/Passive RIS	pilot-overhead	Dual-Stage Neural Network	Effectively reduces pilot overhead while accurately estimating cascaded channels.
[192]	2024	MIMO/Passive RIS	pilot overhead	Pilot Design Optimization with Deep Learning	Minimizes training symbols while maintaining high estimation accuracy.
[193]	2023	MIMO/Passive RIS	pilot overhead	Generative Adversarial Networks (GAN)	Reconstructs high-resolution channel estimates from low-resolution data, reducing pilot overhead.
[194]	2024	MIMO/Passive RIS	Static phase	Neural Network for Phase Shift Optimization	Dynamically adjusts phase configurations to enhance signal quality and reduce training overhead.
[195]	2024	MIMO/Passive RIS	pilot overhead	Deep Learning for Pilot-Aided Estimation	Significantly reduces required pilots while achieving better NMSE performance than conventional methods.
[196]	2024	MIMO/Passive RIS	beamforming and phase shift	Adaptive Deep Learning Models	Adjusts dynamically to varying channel conditions, reducing complexity and pilot overhead.
[197]	2022	mmWave MIMO/RIS	Pilot training overhead	Two-stage channel estimation Least Square Estimation, Kalman Filtering	Demonstrated improved accuracy and reduced overhead in channel estimation processes.
[198]	2023	MIMO/semi-Passive RIS	phase shift	Deep learning techniques (DNN, CNN, RNN, GAN)	Enhanced channel estimation performance, particularly in RIS-aided systems, with significant gains in SNR.
[199]	2021	MIMO/semi-Passive RIS	Pilot overhead	Compressive sensing + deep learning methods	Achieved efficient channel estimation with reduced complexity and improved performance metrics.
[200]	2021	MIMO/semi-Passive RIS	phase shift	Deep Learning for Channel Estimation (CNN, RNN)	Highlighted the effectiveness of deep learning in improving channel estimation accuracy in complex environments.
[201]	2020	MIMO/semi-Passive RIS	Dynamic environments	Deep Reinforcement Learning (DRL) Algorithms	Enabled standalone operation with improved adaptability and efficiency in channel estimation tasks.
[202]	2021	MIMO/semi-Passive RIS	Training overhead	Deep Residual Networks (ResNet) for Channel Estimation	Showed significant improvements in estimation accuracy and robustness against noise.
[203]	2024	MIMO/semi-Passive RIS	Phase-shift and Beamforming problem	Sequential Prediction Algorithms, Kalman Filtering Techniques	Proposed a novel approach for sequential estimation leading to better predictive performance and lower error rates.

2.9 Summary and Research Gap

This chapter is a comprehensive literature review covering key aspects of channel estimation for 5G and beyond communication systems, with a focus on Reconfigurable Intelligent Surfaces (RIS). It begins with an introduction to next-generation wireless networks, emphasizing Terahertz communications and channel fading models, specifically Rayleigh, Rician, and AWGN small-scale fading models. The chapter then delves into cascaded and separate channel estimation methods for RIS-MIMO systems, exploring various signal processing algorithms, including conventional, optimization-based, compressed sensing-based, and deep learning-based approaches. Furthermore, different RIS architectures for channel estimation, such as semi-passive and fully-passive RIS systems, are discussed, along with the combination of cascaded and separate estimation techniques. The review also examines channel estimation for different RIS setups, including single-user, multi-user, and double/multi-RIS systems. Special attention is given to deep learning approaches for super-resolution channel estimation. The chapter concludes with discussions on dataset generation using 5G link-level and system-level simulators, performance metrics, and related works on channel estimation for SRIR-CNN algorithms and cascaded/separate channels. Therefore, to further improve the uplink/downlink RIS-MIMO systems' performance, Channel estimation in RIS-MIMO systems presents greater challenges compared to traditional active device-based MIMO systems for several reasons. Firstly, in active device-based systems, CSI acquisition can be achieved by sending training sequences. In contrast, for RIS-MIMO systems, channel estimation can only be performed at the active transceivers, as RIS is a passive device without active transmitting or receiving capabilities. Secondly, RIS typically has a large number of reflective elements (REs),

which leads to significant training pilot overhead. Finally, it is difficult to independently recover the CSI for the transmitter-RIS and RIS-receiver channels, as they are coupled through the reflection coefficient matrix. This thesis tackles the above challenges, the proposed mechanisms are presented in Chapter 3 in detail.



CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter describes the effective channel estimation techniques to achieve the stated research objectives. The detailed procedures for each method are presented to ensure that the optimal solutions for estimating the channel are completed, with the analysis of the cascaded and separate channels in RIS-MIMO scenarios. The chapter is organized as follows: Section 3.2 introduces the RIS_MIMO systems design. Section 3.3 models the channel using different fast fading. Section 3.4 presents Deep learning for super-resolution cascaded channel estimation downlink RIS-MIMO. Section 3.5 presents the proposed Deep learning design for cascaded and separate uplink/downlink channels in RIS-MIMO systems. Section 3.6 concludes the chapter.

3.2 Research Design for RIS-MIMO Systems

Based on the thesis objectives listed in Chapter 1, this section describes the design procedures of channel estimation techniques in RIS-MIMO systems. The proposed methods to achieve this thesis's main goal are divided into four stages, as shown in Figure 3.1. In the first stage, the channel time-frequency response is modeled as a 2D image using the least square estimator with a new pilot pattern design for different types of multipath fading to achieve the initial goal. These stage details are described in Section 3.3.1, Section 3.3.2, and Section 3.3.3.

In the second stage, the mean square error must be minimized for the downlink cascade channels in RIS-MIMO. The SRIR-ChNet algorithm is utilized to improve the low-resolution image to a high-resolution image to achieve the second goal. These stage details are described in Section 3.3.1, Section 3.4.1, and Section 3.4.2.

In the third stage, high data rate performance must be achieved for the uplink/downlink RIS-MIMO systems. The phase shift and beamforming channel matrix (PSBA-H) network is utilized to obtain optimal phase shift and beamforming matrix. The PSBA-H approach is used to improve the channel estimation capacity for two scenarios the cascade and separate channels to achieve the third goal. The details of this stage are described in Section 3.3.1, Section 3.5.1, Section 3.5.2, and Section 3.5.3.

In the fourth stage, The performance of each proposed channel estimation method in RIS-MIMO is assessed using a comprehensive set of performance metrics such as time complexity and normalized mean square error to achieve the last goal. The details of this stage are described in Section 3.6.

The proposed channel estimation schemes are developed using MATLAB simulator and Anaconda (Spyder) to achieve a high data rate and accurate CSI performance for the RIS-MIMO systems.

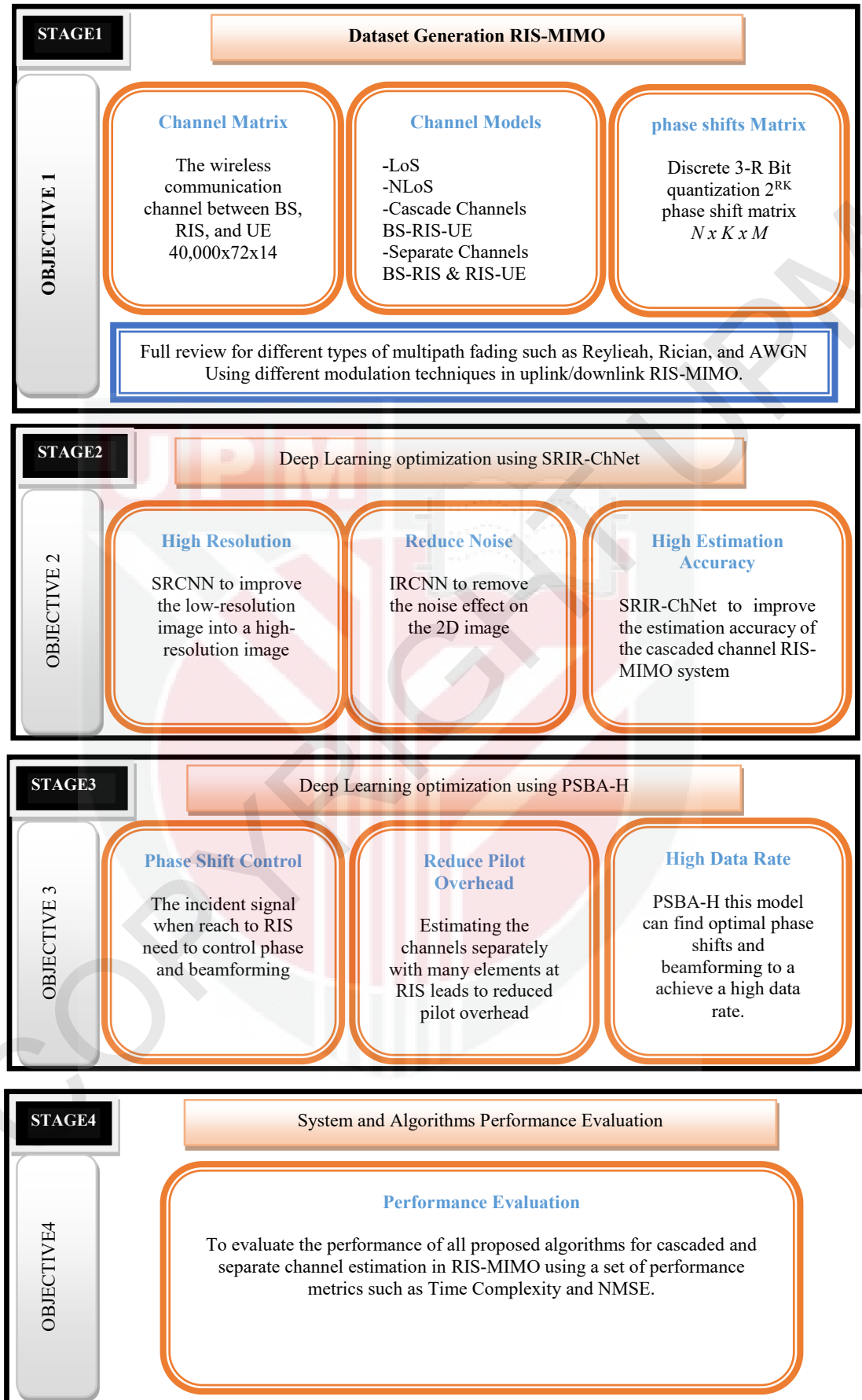


Figure 3.1: Research design stages

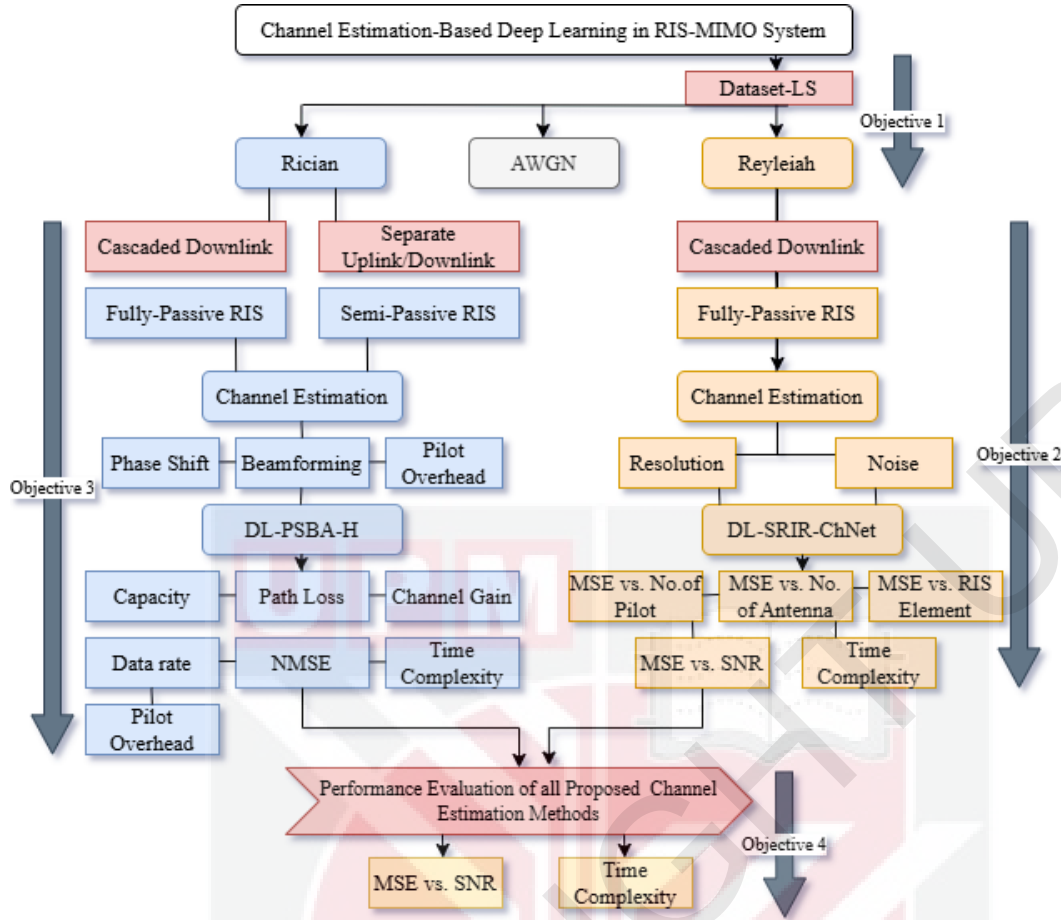


Figure 3.2: Comprehensive Framework for Deep Learning-Based Channel Estimation in RIS-MIMO Systems

3.3 Channel Estimation Using Least Square for Different Fast-Fading Channel Models

This section describes the channel estimation process in a wireless communication system utilizing the Least Square (LS) algorithm with a new proposed diamond pilot pattern to solve channel estimation problems in direct and reflected paths. The estimation will be performed using different fast-fading channel models, including Rayleigh, Rician, and Additive White Gaussian Noise (AWGN). A details description of the system model is given in section 3.3.1.

3.3.1 System Model

This section presents a comprehensive review of multipath Rayleigh and Rician channel models. Additionally, it examines the performance of OFDM systems, both with and without channel estimation, across AWGN, Rayleigh, and Rician channel environments, we propose a system model for channel estimation using Least Square (LS) with a new diamond pilot pattern across three distinct multipath fading environments: Rayleigh, Rician, and AWGN.

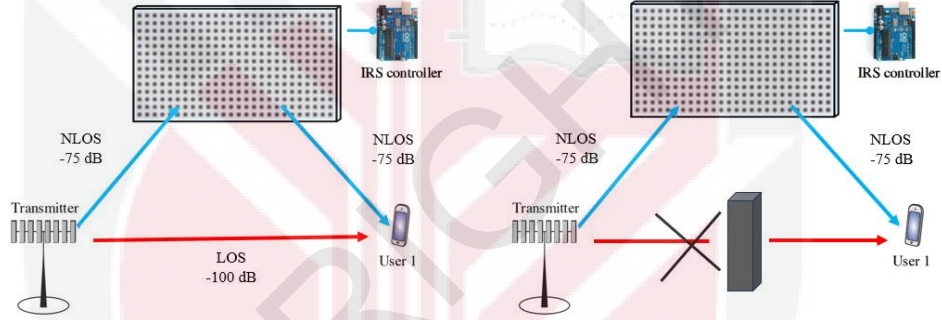


Figure 3.3: The proposed uplink/downlink RIS-MIMO for multipath fading

The values -75 and -100 dB represent the channel gain at a reference distance, often taken from real-world measurements or standard models such as the 3GPP path loss models [198]. The **Rayleigh** fading model is employed to simulate environments in environments lacking a direct line-of-sight path between the transmitting and receiving devices. This model is particularly relevant in urban settings with numerous scatterers.

$$\mathbf{h}_K^{NLOS} \sim \mathcal{N}_c(\mathbf{0}, \mathbf{I}_M), \quad (3.1)$$

However, in practical systems, the channel is generally spatially correlated, leading to correlated Rayleigh fading models as [50]

$$\mathbf{h}_K^{NLOS} \sim \mathcal{N}_c(\mathbf{0}, \mathbf{R}), \quad (3.2)$$

Where $\mathbf{R} \in \mathbb{C}^{M \times M}$ is the positive semi-definite spatial correlation matrix. Besides, since the propagation environment is complex, both the LoS and the NLoS channel components could exist in practical systems. Therefore, a more general channel fading model is the uncorrelated/correlated **Rician** fading model, given by [50]

$$\mathbf{H}_{k,n} = \sqrt{\frac{k_{k,n}}{k_{k,n}+1}} \mathbf{h}_{k,n}^{(LOS)} + \sqrt{\frac{1}{k_{k,n}+1}} \mathbf{h}_{k,n}^{(NLOS)}, \quad (3.3)$$

Where $k_{k,n}$ is the Rician factor that shows the power ratio between the LoS channel component and the NLoS channel component. $k_{k,n}$ could be large if there are few scatterers in the propagation environment. The **AWGN** model serves as a baseline to analyze the impact of noise on channel estimation, representing the thermal noise present in communication systems. The system model stages are shown in Figure 3.4.

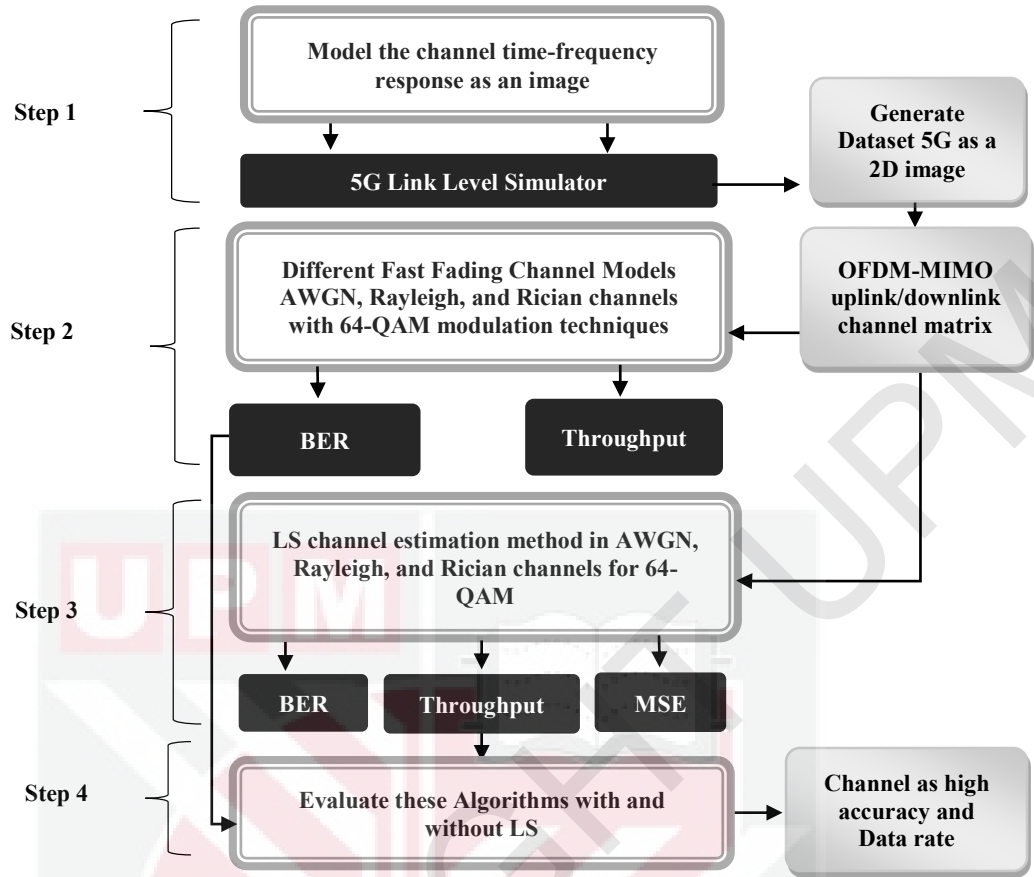


Figure 3.4: Methodology of the proposed system model

3.3.2 Channel Model

In the first step of generating a dataset for channel estimation, The Vienna 5G Link Level Simulator is employed to generate an image representation of the channel's time-frequency response. This simulator is a powerful tool designed for simulating various aspects of mobile communications, particularly focusing on the physical layer (PHY) of the communication system. The process begins by configuring the simulator to define key parameters such as the number of frames, subcarriers, and time slots, which will determine the dimensions of our dataset. For instance, we might set up a scenario with 40,000 frames, 72 subcarriers, and 14 time slots. The simulator allows for the implementation of different multipath fading models, including Rayleigh, Rician, and

AWGN, which are critical in simulating realistic wireless environments. The two key parameters for this model are K and Δ . They can be added to a scenario file in the following way:

Table 3.1: Channel Parameters

Fading Statistic	K	Δ
No Fading	∞	0
Rician	> 0	0
Rayleigh	0	$\sim$

The parameter K represents the power ratio between the specular and diffuse components and is always positive. The parameter Δ is related to the ratio between peak and average specular power and thus describes the power relationship between the two specular components, and is limited to the interval from 0 to 1.

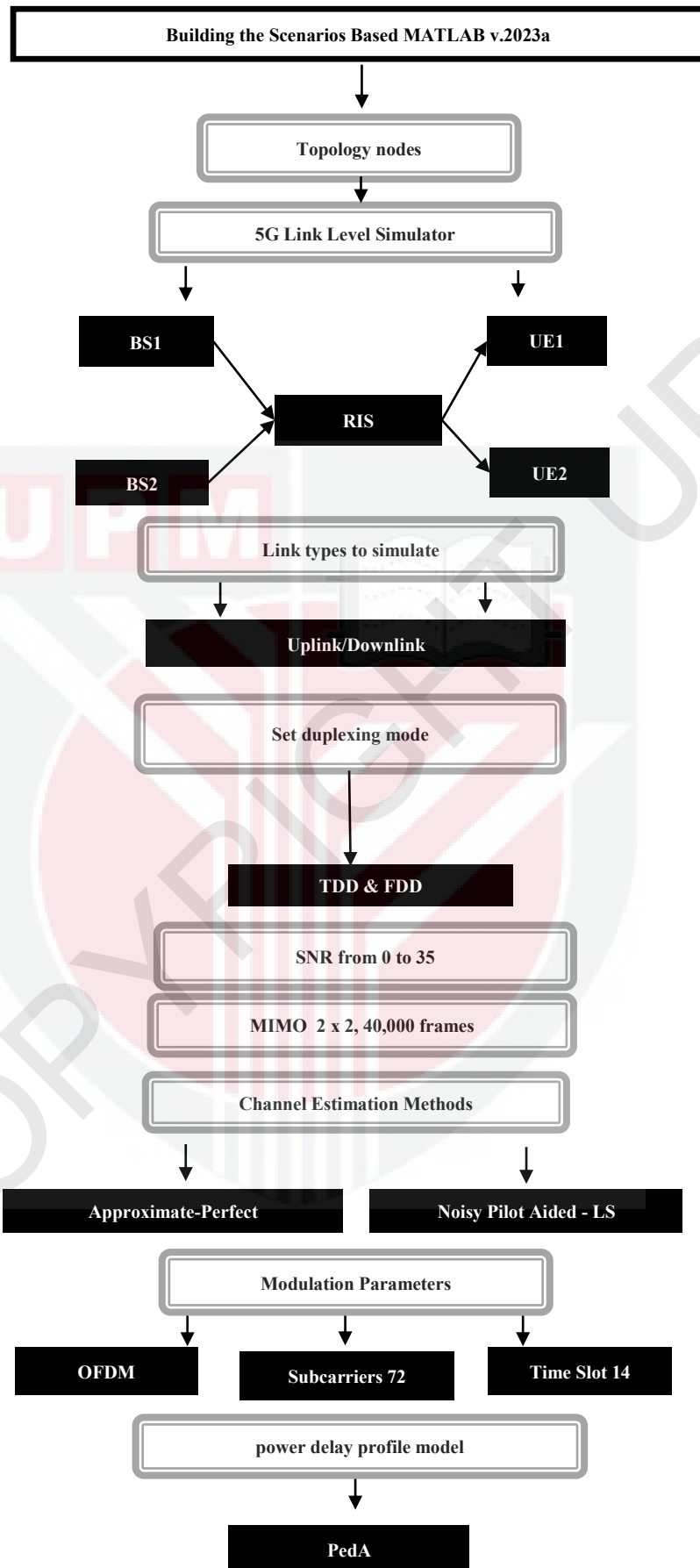
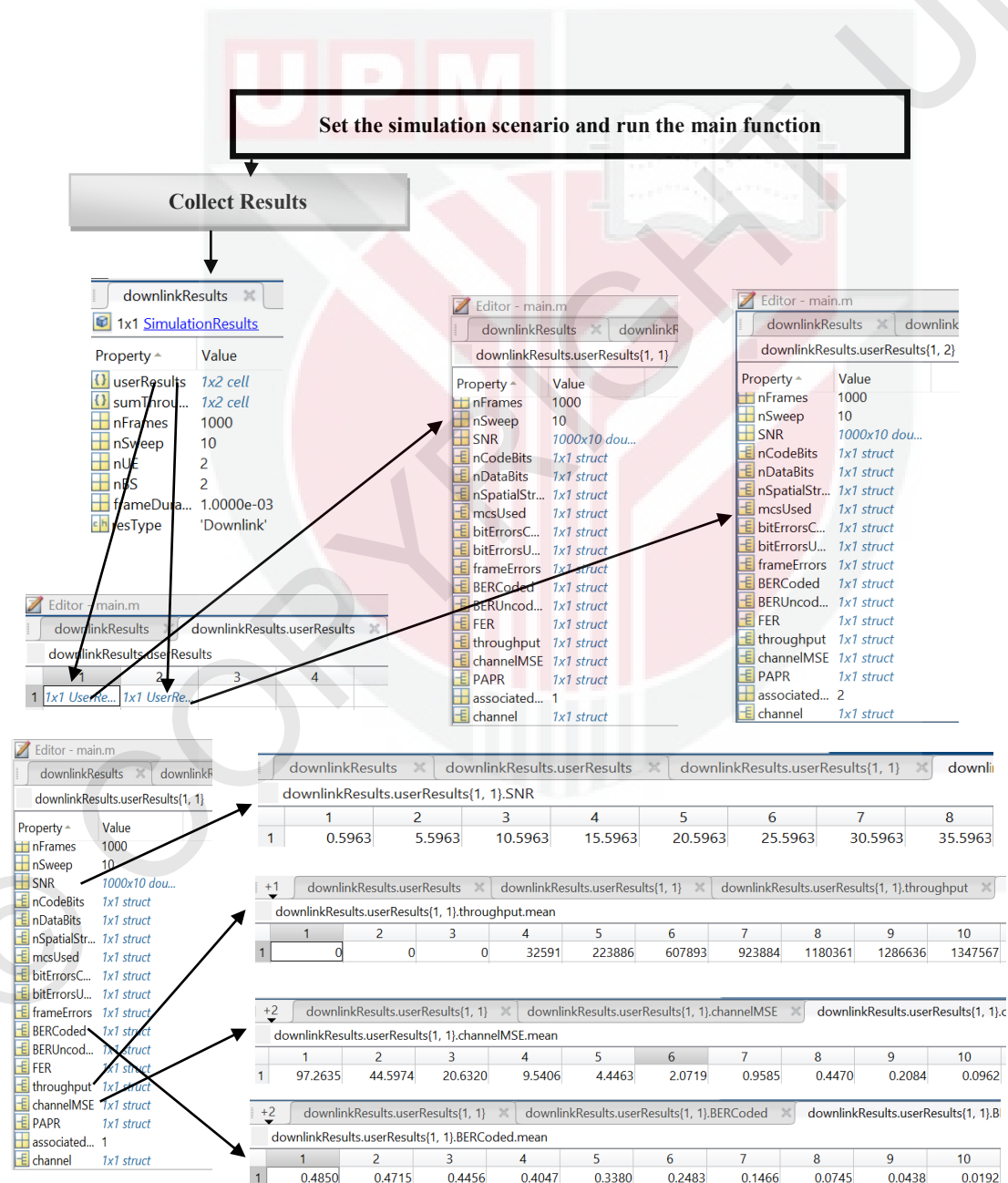


Figure 3.5: Simulation Setup

After setting the simulation scenario and running the main function, we collect various datasets as in Figure 3.6 for three types of multipath fading channel models AWGN, Rayleigh, and Rician while employing 64-QAM as the modulation technique for our wireless communication system with and without channel estimation methods which means all the channels are close to the ideal channel, these channels are used to evaluate the same fading with noisy channel using least square with a diamond pilot pattern for different modulation techniques in uplink/downlink.



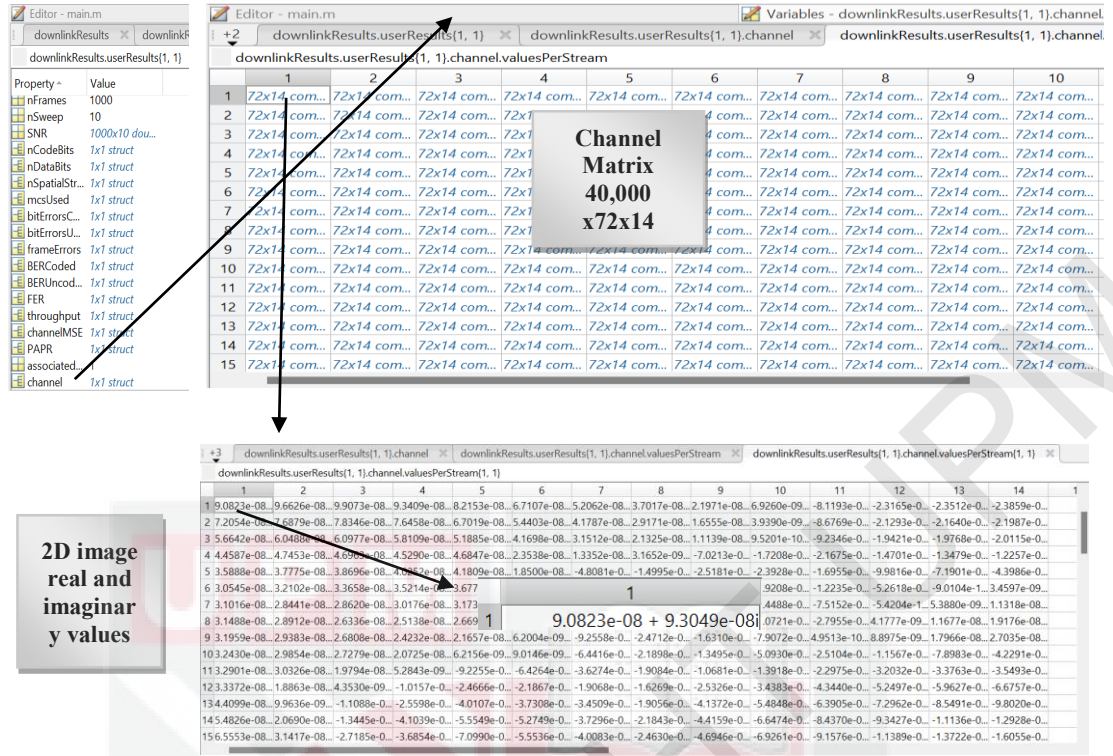


Figure 3.6: Simulation Scenario results

In this study, we focus on multiple links between two pairs of Tx and Rx antennas, i.e., For multiple-input, multiple-output (MIMO) communication links, we define the channel time-frequency response matrix H , of size $N_S \times N_D$, to describe the channel between a transmitter and a receiver, which has complex values, can be represented as two 2D images (one 2D image for real values and another one for imaginary values). An example of the normalized real/imaginary 2D image for a sample channel time-frequency grid with $N_D = 14$ time slots and $N_S = 72$ subcarriers (based on the 5G standard) is shown in Figure 3.7.

The image in Figure 3.7 depicts a 2D matrix representing the channel response in a wireless communication system. This matrix denoted as H , is typically used to model the propagation characteristics between a transmitter and a receiver.

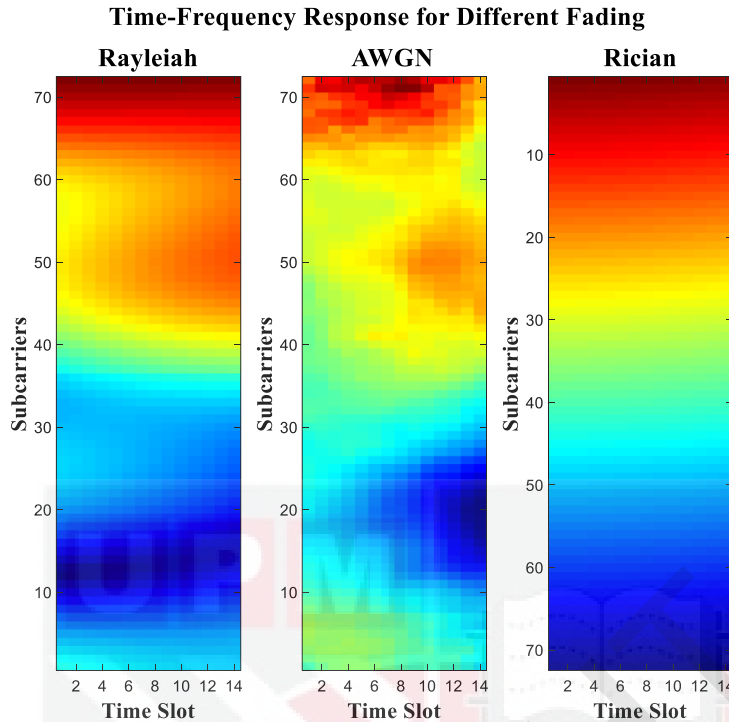


Figure 3.7: Channel Matrix in size 72 x 14 2D image time-frequency

The dimensions 72 Rows: Represent the subcarriers in an Orthogonal Frequency Division Multiplexing (OFDM) system and 14 Columns: Represent the time slots or symbols within a data frame. The colors in the image represent the magnitude of the channel coefficients. A common color scheme used in such visualizations is:

- Blue and Dark Blue: Low magnitude (weaker channel responses and signal power).
- Yellow and Green: High magnitude (the signal is neither too strong nor too weak).
- Red and Orange: Very high magnitude (stronger channel responses and signal power).

Interpretation:

- Darker Regions: Indicate weak channel conditions, potentially leading to signal attenuation or fading or Strong channel.

- **Brighter Regions:** Indicate strong channel conditions, which can be beneficial for reliable communication or moderate channels.
- **Patterns and Trends:** The image can reveal patterns and trends in the channel response, such as frequency selectivity, time-varying effects, or the presence of multipath.

The image visually represents the channel's behavior in both time and frequency domains. Figure 3.7 represents distinct fading conditions. The PSBA-CNN model: The input matrix is derived from a Rician fading channel, which includes a dominant line-of-sight (LOS) and non-line-of-sight (NLOS) component along with multipath scattering. The SRIR-ChNet model: The input matrix is based on a Rayleigh fading channel, which assumes a purely non-line-of-sight (NLOS) environment where multipath scattering dominates. AWGN is a type of thermal noise that affects the direct path of the signal. However, since we focus on reflected path characteristics, we did not explicitly apply AWGN in any deep-learning model. The differences in these matrices are crucial because the deep learning models are designed to learn and extract distinct channel features specific to Rician and Rayleigh scenarios. This differentiation ensures that the models are optimized for their respective channel conditions, improving channel estimation accuracy.

3.3.3 Performance Metrics

Different performance metrics are usually deployed to evaluate every wireless communication system's performance. In this section, the following performance metrics are evaluated and analyzed: Throughput (achievable data rate), Bit Error Rate, and Mean Square Error.

3.3.3.1 Throughput

Throughput is the effective data rate at which information is successfully transmitted over a communication channel, typically measured in bits per second (bps). It can be mathematically expressed as [204]:

$$C = \log_2 \det(I + \frac{P}{N_0} H) \quad (3.4)$$

Where C is the achievable data rate (in bits per second), H is the channel matrix, P is the total transmit power, N_0 is the noise power spectral density, I is the identity matrix, and $\det$ denotes the determinant.

3.3.3.2 Bit Error Rate (BER)

The Bit Error Rate quantifies the ratio of erroneous bits to the total number of transmitted bits, providing insight into the reliability of a communication system. It is calculated as [204]:

$$BER = \frac{1}{2} \operatorname{erfc} \left(\sqrt{\frac{E_b}{N_0}} \right) \quad (3.5)$$

Where erfc is the complementary error function. E_b is the energy per bit. N_0 is the noise power spectral density. In RIS-MIMO systems, the BER can also be affected by the quality of channel estimation. A lower MSE in channel estimation typically results in a lower BER.

3.3.3.3 Mean Square Error (MSE)

Mean Square Error assesses the accuracy of an estimated signal compared to the actual transmitted signal. It can be expressed mathematically as [204]:

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{h}_i - h_i)^2 \quad (3.6)$$

where h_i is the actual channel response and $\hat{h}_i$ is the estimated channel response. N is the number of channel coefficients. In RIS-MIMO systems, MSE plays a vital role in evaluating channel estimation performance under multipath fading conditions. A lower MSE indicates more accurate channel estimation, which is crucial for optimizing system performance. These performance metrics Throughput, BER, and MSE are essential for analyzing and enhancing the efficiency and reliability of wireless communication systems operating in multipath fading environments.

3.4 Channel Estimation using SRIR-ChNet for Super-resolution and Image restoration based on Downlink Cascaded Channel

Accurate channel estimation in a RIS-MIMO system necessitates the treatment of the channel state information (CSI) estimation problem as an image super-resolution (SR) task, which reconstructs and denoises the channel matrix. We therefore propose SRIR-ChNet, a deep learning model that incorporates both a super-resolution convolutional neural network (SRCNN) and an image restoration convolutional neural network (IRCNN). The estimated channels at pilot locations are processed as a low-resolution image, enabling the enhanced SRCNN to effectively capture input features and learn an appropriate interpolation strategy, which yields a coarse channel matrix estimate. Following this, the IRCNN denoising model employs element-wise subtraction to extract noise characteristics and improve the channel coefficients derived from the

coarse estimate. Deep CNNs have demonstrated their capability to transform low-resolution images into high-resolution ones [205, 206]. Recent studies have explored the use of SRCNN for comprehensive low-resolution image reconstruction [207, 208]. Additionally, various image restoration (IR) approaches [209,211] have been developed to counteract noise effects. Furthermore, studies [212, 213] present methodologies designed to optimize the training efficiency of feed-forward denoising convolutional neural networks (DnCNNs).

3.4.1 System and Channel Model

We consider a downlink cascaded channel in the RIS-MIMO system, as presented in Figure 3.8, where the RIS supports two BS and two UE. The BS is equipped with an N antenna array, and the RIS, a fully passive reconfigurable intelligent surface, is composed of K reflecting elements, assisting both the BS and the multi-antenna users. Both the BS antenna array and the RIS reflecting elements are organized in a uniform linear array (ULA) configuration. Additionally, the BS manages a controller that dynamically adjusts the propagation environment, as depicted in Figure 3.8, $H_{T,K,R}$ where $H \in \{1, 2, \dots, h\}$, represent the channels of BS-RIS, and RIS-UE respectively. The channels $H_{T,K}$, and $H_{K,R}$ are modeled as Rayleigh fading channels. Furthermore, the system operates in a Frequency-Division Duplex (FDD) mode to leverage channel reciprocity (CR). Utilizing the CR principle, the Base Station (BS) is capable of predicting downlink channels through FDD, which entails configuring channels for downlink pilot reception. The system model's stages for the downlink RIS-MIMO system are depicted in Figure 3.9. The channel is modeled according to the specifications in Section 3.3.2, which includes Rayleigh fading characteristics.

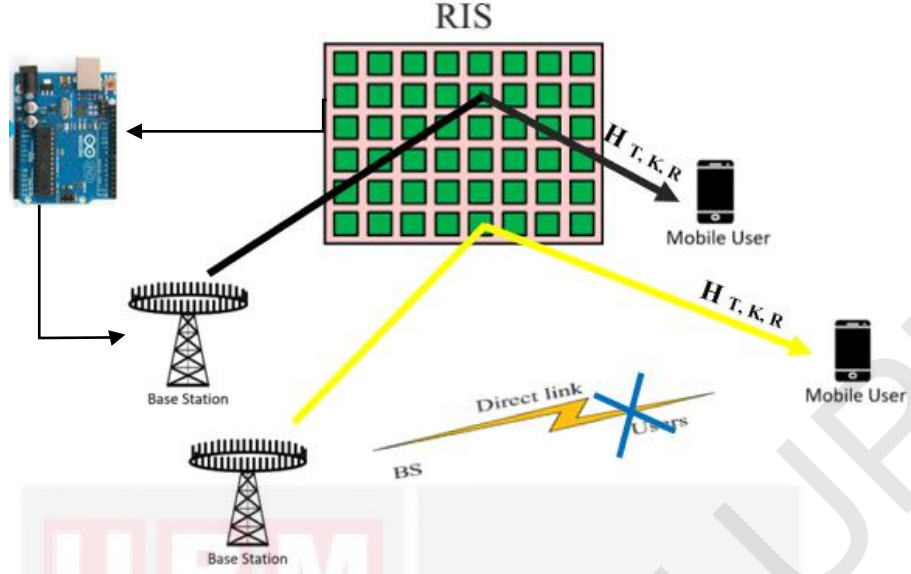


Figure 3.8: Proposed RIS-MIMO downlink Communication System Model

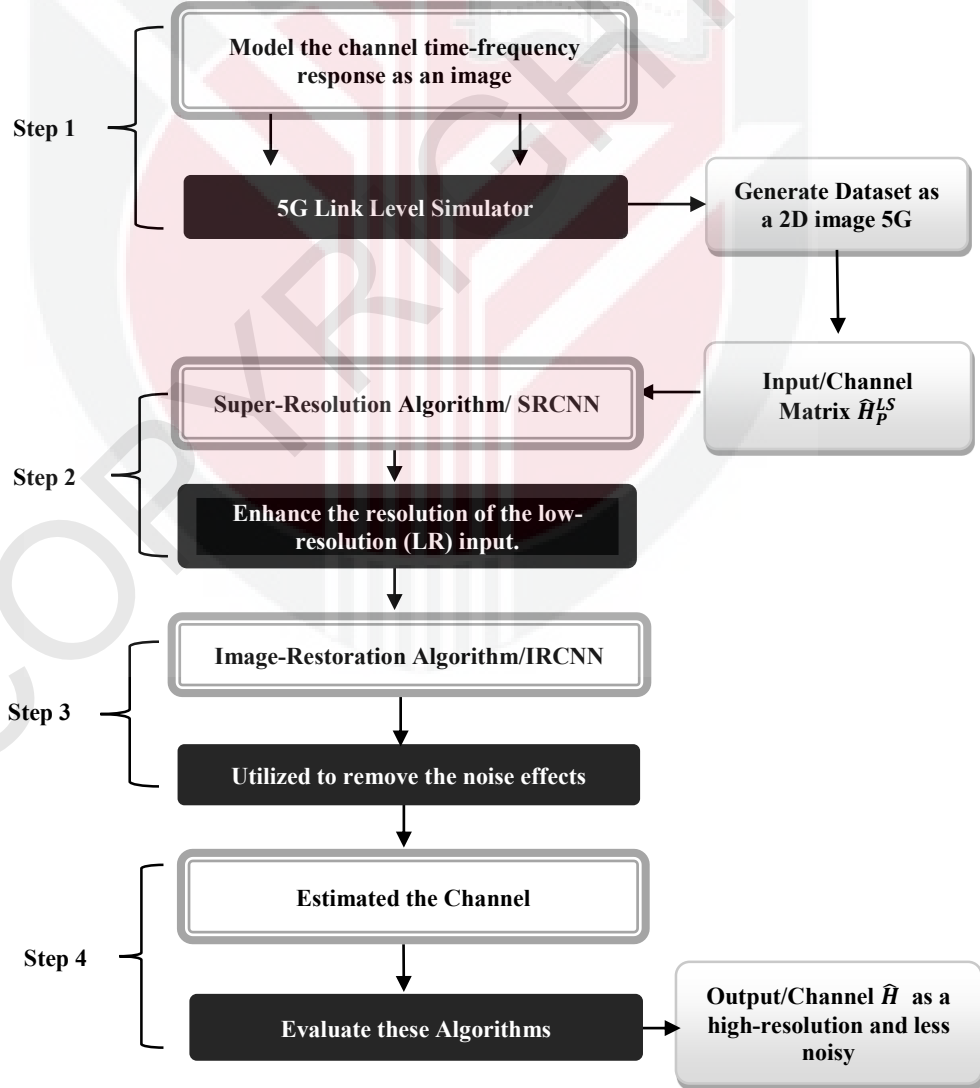


Figure 3.9: Methodology Channel Estimation Solution for SRIR-ChNet

3.4.1.1 Conventional Channel State Information Estimator

The Least Square (LS) channel estimator determines $\hat{H}$ by minimizing a cost function.

At pilot tones, this determination is defined as [188]

$$\hat{H}_p^{LS} = \arg \min \|y_p - x_p \hat{H}\|^2 \quad (3.7)$$

The estimated channel at specific positions within each OFDM symbol, denoted as $\hat{H}_p^{LS} \in \mathbb{C}^{N_p \times L}$, is obtained using the least square (LS) estimator. To determine the channel coefficients at other positions, interpolation techniques such as linear interpolation are applied, which do not require prior channel knowledge. Due to its simplicity and effectiveness, the LS estimator is widely utilized. Furthermore, to enhance channel estimation performance, we incorporate a discrete Fourier transform (DFT)-based technique.

3.4.1.2 Network Structure and Training

The estimated value of the channel H_p the pilot positions are treated as a low-resolution (LR) and noisy channel image because they represent incomplete and noisy observations of the channel. The SRCNN model processes these inputs to upsample and refine them into a denser representation, while the IRCNN stage further enhances the quality by reducing residual noise. The initial resolution of the channel image is defined by the number of sparse pilot positions in the time-frequency grid, where pilots are placed at specific intervals to sample the channel matrix. For example, if the channel matrix size is 72×14 and pilots are sparsely placed, the low-resolution (LR) image contains only the sampled values at these pilot locations, leaving the rest of the

grid unfilled or zero. This LR noisy image is then input into the SRCNN network, which utilizes the estimated channel values as a vector representation of a low-resolution input image. Since this vector representation encompasses both real and imaginary components, the image is processed in two stages within the SR network: the first stage focuses on the real part, while the second stage addresses the imaginary part. The target criteria for the image resolution when SRCNN is implemented involve reconstructing a high-resolution (HR) channel image that fills in the missing entries in the grid while accurately approximating the true channel response. This is achieved by: interpolating the sparse pilot positions to generate a denser grid, effectively increasing the spatial and frequency resolution of the channel matrix. Reducing noise introduced during the channel estimation process ensures the reconstructed HR image closely matches the ground-truth channel. Minimizing reconstruction error, the target is to achieve the highest possible accuracy, typically measured by metrics such as mean squared error (MSE), ensuring the reconstructed channel matrix aligns with the true channel's characteristics.

The SRCNN model addresses these criteria by learning the mapping from the LR noisy image (pilot-based channel estimate) to the HR denoised image, providing a refined channel matrix for better performance in RIS-MIMO systems. The primary goal of the SR network is to estimate the unknown values of the channel response, denoted as $h \sim n$ to further mitigate noise effects, an Image Restoration (IR) network is subsequently integrated with the SR network. In the SRIR-ChNet framework, the SR network initially used an approximation technique to identify the approximate values of an image. Subsequently, it recovers an LR image that is as close to the original HR image as possible.

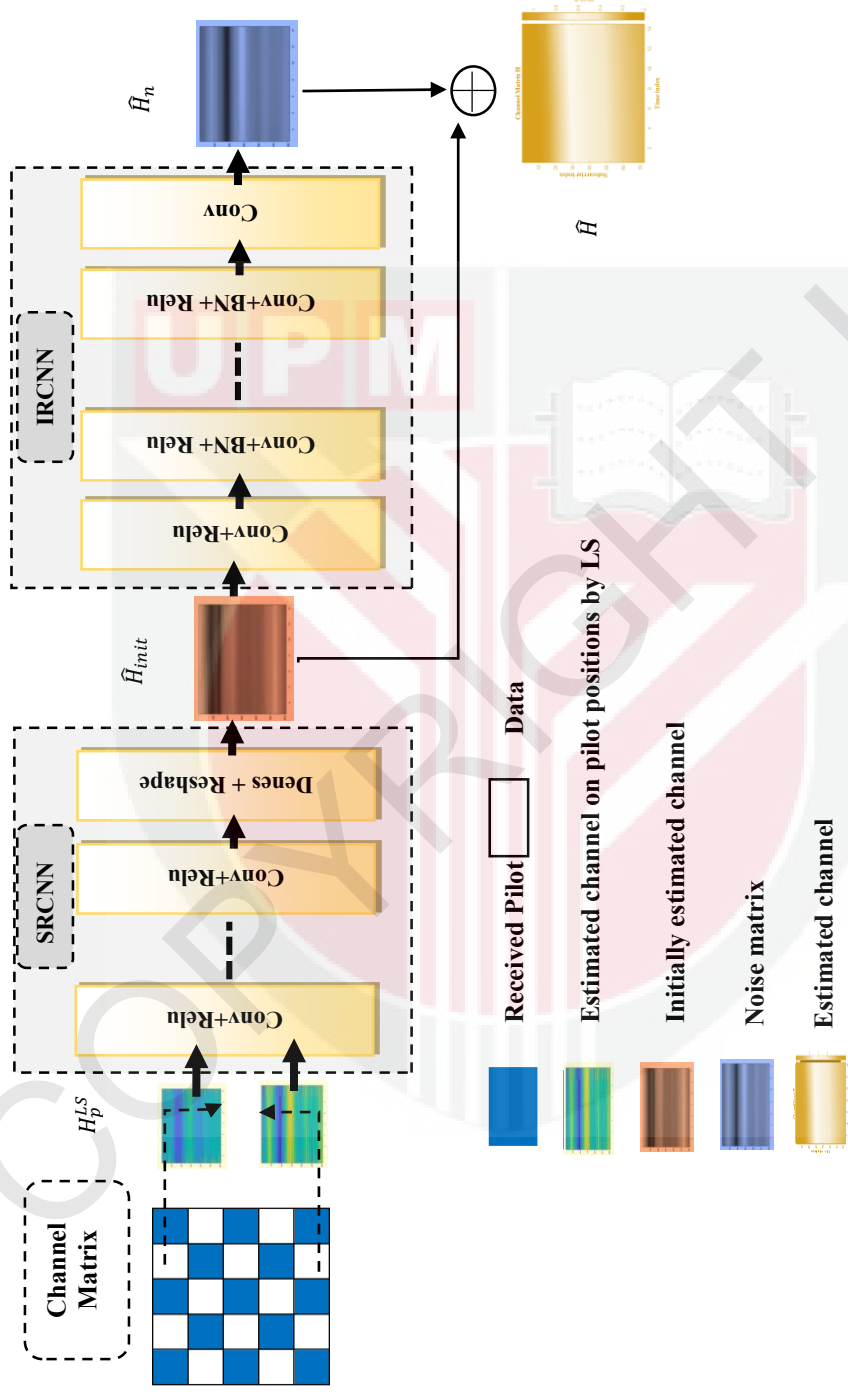


Figure 3.10: A general pipeline of the proposed SRIR-ChNet with a combination of SRCNN and IRCNN for channel estimation in RIS-MIMO systems

However, to accomplish this, the main purpose is to learn a mapping F , which consists of three operations: a feature extractor, nonlinear mapping, and reconstruction [214]. An end-to-end model called SRIR-ChNet is introduced, as depicted in Figure 3.10. SRIR-ChNet integrates both SRCNN and IRCNN. To facilitate the effective capture of complex input features, the input layer is designed with two channels. The initial layer of SRCNN functions as a feature extraction and representation phase, identifying key patterns in low-resolution data and transforming them into a higher-dimensional space. The second layer applies a nonlinear mapping to convert each feature map into a high-dimensional representation corresponding to a high-resolution patch. In the final stage, the third layer integrates these patches, resulting in a refined high-resolution output that differs in size from the ground truth channel, since no initial interpolation is carried out. A dense layer and a reshaping layer are then implemented to yield an initial estimate, denoted as $\hat{H}_{init}$, which matches the size of the ground truth channel. Unlike the typical up-sampling layer, which is not learnable, this method employs a trainable dense layer, facilitating a learnable aggregation of all features to estimate the actual channel. Given the correlation of channels across transmitted symbols within the coherence time, each pixel in the dense layer's output is linked to the high-dimensional representation of all estimated channels at pilot positions. This design allows SRIR-ChNet to surpass CAE-ChannelNet in performance. In essence, SRCNN extracts high-dimensional features from the low-resolution image (H_p^{LS}), and combines these features to reconstruct the high-resolution estimate $\hat{H}_{init}$. Simultaneously, the SRCNN is able to find a suitable interpolation method, which overcomes the limitations of linear or polynomial approaches, leading to increased interpolation accuracy. We then incorporate the IRCNN, a proven denoising model, in a cascaded design with SRCNN to enhance performance. The IRCNN learns the

features of the coarse channel matrix generated by SRCNN, alongside the additive noise, and its element-wise subtraction before the output produces a refined denoised estimation ($\hat{H}$). The hyperparameters for SRIR-ChNet are specified in Table 3.2. These parameters adhere to the default configurations found in [214] and [215]. The principal aim of this research is the estimation of Reconfigurable Intelligent Surface (RIS) channels using received pilot signals. In this context, the deep learning (DL) method requires specific inputs and outputs for effective pilot-based channel estimation: the received pilots serve as the input, while the estimated channels represent the output. To facilitate pilot transmissions, a lattice-patterned framework, similar to that used in the 5G standard, has been implemented. The channel representation, which is characterized by low fidelity and potential interference, corresponds to the expected channel values at the pilot points. This is denoted as $\hat{H}_P^{LS}$ to obtain a comprehensive channel image, we introduce a one-phase with two stages training approach designed to enhance the accuracy of the channel estimation process:

- i. In the initial stage, a Super-Resolution (SR) network is developed. This network utilizes $\hat{H}_P^{LS}$ as the vectorized low-resolution input, processing the real part first, followed by the imaginary part, to estimate the unknown channel response values, denoted as H .
- ii. In the subsequent stage, a noise-reducing Image Restoration (IR) network is integrated with the SR network to effectively reduce noise interference.

The SRCNN [214] was employed for super-resolution (SR) tasks, while the DnCNN [215] was utilized for image restoration (IR) functions. The SRCNN utilizes a three-layer convolutional network to enhance images to approximate high-resolution values for the image (or channel). In the first convolutional layer, which follows a ReLU activation, 64 filters of size 9×9 are used. The second layer consists of 32 filters, each

measuring 1×1 . Finally, the output is reconstructed using a single filter of size 5×5 in the last layer.

The IRCNN network is built on residual learning and consists of 20 convolutional layers (further details are provided in [216]). The first layer utilizes 64 filters of size 3×3 , followed by a ReLU activation function. The subsequent 18 convolutional layers also use 64 filters of size 3×3 , with each layer followed by batch normalization and ReLU activations. The final layer reconstructs the output using a single filter of size 3×3 . For SR and IR networks, the training rate is set to 0.001 with a batch size of 128 and at most 400 iterations. The training, testing, and validation sets consist of 30000, 5000, and 5000 channels, respectively.

Table 3.2: Settings of SRIR-ChNet

Input	SRCNN		IRCNN		Output
	<i>Layers</i>	<i>Filter Size</i>	<i>Layers</i>	<i>Filter Size</i>	
Estimated channels at pilot positions.	1	$64 \times (9 \times 9 \times 2)$	1	$64 \times (3 \times 3 \times 2)$	Estimated whole channel.
	2	$32 \times (1 \times 1 \times 64)$	2-19	$64 \times (3 \times 3 \times 64)$	
	3	$2 \times (5 \times 5 \times 32)$	20	$2 \times (3 \times 3 \times 64)$	

Algorithm 1 provides a summary of the SRIR-ChNet-based channel estimation process. In this context, 'i' signifies the loop index, and 'Epoch' represents the maximum number of iterations.

Algorithm 1: The proposed Channel Estimation with SRIR-ChNet

Initialization: Let denote the set of all network parameters by $\Theta = \{\Theta_S, \Theta_R\}$, where the Θ_S and Θ_R denote the set of parameter values for SR and IR networks, respectively.

Offline Training:

1. **Input:** 30000 frames (the pilot values matrix $\hat{H}_P^{LS}$)
2. While $i \leq \text{epoch}$ (400 iterations)
3. Update trainable parameters Θ by Adam
4. $i = i + 1$
5. **Output:** Well-trained model $f(I, \Theta^*)$

Online Prediction:

6. **Input:** 5000 and 5000 testing and validation sets
 7. Estimate channel by using well-train SRIR-ChNet
 8. **Output:** Estimated channel matrix is denoted as $H_{\text{SRIR-ChNet}}$
-

The CAE-ChannelNet [199] model, which employs an image super-resolution (SR) approach for channel estimation, is not without its limitations:

- i. **Dependence on Interpolation Methods:** The performance of CAE-ChannelNet is significantly influenced by the choice of interpolation methods used. Variations in these methods can lead to inconsistent results in channel estimation.
- ii. **Increased Input Size and Computational Complexity:** Following the initial interpolation, the input's dimensions are expanded beyond the original input's size, which substantially increases computational complexity. This can lead to longer processing times and higher resource consumption.
- iii. **Not an End-to-End Model:** CAE-ChannelNet is not an end-to-end model; rather, it undergoes training in two separate stages. This multi-stage training approach may limit its efficiency and complicate the overall training process.

The use of convolutional neural networks (CNN) for channel estimation is justified primarily because the dataset is represented as a 2D image, specifically a time-frequency grid. CNNs are particularly well-suited for tasks involving structured data like images, where spatial relationships and patterns play a significant role.

3.4.2 Performance Metrics

Several key performance metrics are employed to evaluate the effectiveness of super-resolution channel estimation in wireless communication systems. These metrics provide valuable insights into the accuracy and reliability of the channel estimates, which are crucial for optimizing overall system performance. The primary metrics considered in this context include Mean Square Error (MSE) vs. signal-to-noise ratio (SNR), MSE vs. Number of Pilots, MSE vs. Number of Antennae, MSE vs. Number of RIS Elements, as well as aspects related to training, testing, validation, and Time Complexity.

3.4.2.1 MSE vs. SNR

Mean Square Error (MSE) is a fundamental performance metric used to evaluate the effectiveness of super-resolution (SR) channel estimation techniques. It quantifies the average squared difference between the estimated channel values and the actual channel values, providing a clear indication of the accuracy of the estimation process. The relationship between MSE and Signal-to-Noise Ratio (SNR) is often analyzed to understand how noise affects channel estimation accuracy. As SNR increases, MSE typically decreases, indicating improved estimation quality. Mathematically, MSE is defined as [217]

$$MSE = \frac{1}{N} \sum_{i=1}^N (\hat{h}_i - h_i)^2 \quad (3.8)$$

3.4.2.2 MSE vs. Number of Pilots

This metric examines how the number of pilot signals used for channel estimation influences MSE. Generally, increasing the number of pilots leads to a reduction in MSE. Analyzing MSE about the number of pilots allows researchers to optimize pilot allocation strategies. More pilots provide richer information for accurate channel estimation, which is crucial for enhancing system performance while managing overhead.

3.4.2.3 Training, Testing, and Validating

When considering deep learning, especially its application to super-resolution channel estimation in wireless communication systems, the processes of training, testing, and

validation are crucial for developing robust models. Each phase plays a distinct role in ensuring that the model can accurately estimate channels under various conditions.

i. Training

Training is the initial phase where the model learns from a dataset containing labeled examples. In the case of channel estimation, this dataset consists of pairs of input data (low-resolution channel estimates) and corresponding target outputs (high-resolution channel values).

Process:

- **Data Preparation:** The training dataset is prepared by collecting pilot signals and their associated true channel values. This data is often split into training and validation sets.
- **Loss Function:** A loss function, typically Mean Square Error (MSE), is defined to measure the difference between the estimated channel values produced by the model and the actual true values. The objective during training is to minimize this loss function [217].

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N (h_i^{est}(\theta) - h_i^{true})^2 \quad (3.9)$$

where θ represents the model parameters. Various optimization algorithms (e.g., Stochastic Gradient Descent, Adam) are employed to update the model parameters iteratively based on the gradients of the loss function. This process continues until convergence is achieved or until a predetermined number of epochs is completed. The training phase is essential for enabling the model to learn patterns from historical data, allowing it to make accurate predictions on new, unseen data. A well-trained model can effectively capture the complexities of channel behavior in varying environments.

ii. Testing

Testing involves evaluating the trained model's performance on a separate dataset that was not used during the training phase. This dataset typically contains unseen examples that help assess how well the model generalizes to new situations.

Process:

Performance Metrics Evaluation: During testing, various performance metrics such as MSE and accuracy are computed to gauge how well the model performs on unseen data [217].

$$MSE_{test} = \frac{1}{N_{test}} \sum_{j=1}^{N_{test}} (h_j^{est} - h_j^{true})^2 \quad (3.10)$$

Where N_{test} is the number of test samples. The results from testing provide insights into the model's ability to generalize beyond its training data. High performance on this dataset indicates that the model can reliably estimate channels in real-world scenarios. Testing is critical for validating that the trained model performs well under different conditions and does not overfit the training data. It ensures that the model can maintain accuracy when faced with new inputs.

iii. Validation

Validation is a process used during training to fine-tune hyperparameters and assess performance metrics without using test data. It typically involves a separate validation set derived from the original dataset.

Process:

Hyperparameter Tuning: During validation, various hyperparameters (e.g., learning rate, batch size, number of layers) are adjusted to optimize model performance. Techniques such as grid search or random search may be employed to find optimal settings.

Performance Monitoring: The validation set is used to monitor performance metrics like MSE and accuracy throughout training. If performance on the validation set begins to degrade while performance on the training set improves (a sign of overfitting), adjustments can be made to prevent this issue [217].

$$MSE_{val} = \frac{1}{N_{val}} \sum_{k=1}^{N_{val}} (h_k^{est} - h_k^{true})^2 \quad (3.11)$$

Where N_{val} is the number of validation samples. Validation helps ensure that models are not only accurate on training data but also capable of performing well in practical applications. This phase allows for early detection of overfitting and helps refine models before they are deployed in real-world scenarios.

3.4.2.4 Time Complexity

In computational complexity theory, complexity serves as a critical measure of how efficiently a program or algorithm can solve a particular optimization problem. This concept is fundamental in understanding the performance and scalability of algorithms, especially as the size of the input data increases. When it comes to Convolutional Neural Networks (CNNs), calculating complexity involves analyzing time complexity. Time complexity refers to the number of operations per second required to perform a forward pass through the network. The complexity of a

convolutional layer is given by the formula:

$$C_{CL} = \mathcal{O}(\mathcal{W}_h \mathcal{W}_w F^2 N_I N_O), \quad (3.12)$$

In this context, $\mathcal{W}_h$ and $\mathcal{W}_w$ represent the height and width of the resulting feature maps, k signifies the filter's side length, and N_I and N_O denote the count of input and output feature maps, respectively.

3.5 Channel Estimation using PSBA-H for optimal phase shift and Beamforming in Uplink/Downlink Cascaded and Separate channels

RIS technology is now essential for developing intelligent and reconfigurable radio spaces in wireless communication systems. This is accomplished through real-time digital control of signal reflections via a large collection of passive reflecting elements. The Reconfigurable Intelligent Surface (RIS) has garnered significant attention [218], with applications spanning secure communications [221], uncrewed aerial vehicles [219], and energy efficiency [220]. Simultaneous optimization of the RIS phase shift and source beamforming is crucial in scenarios where the source node S is equipped with multiple antennas. This optimization necessitates the Channel State Information (CSI) for all links. The S to RIS and RIS to destination (D) links are treated as separate channels, while the end-to-end S to RIS to D link is modeled as a cascaded channel.

This section details the system model designed to address the channel estimation challenge in both uplink and downlink cascaded and separate channels for the RIS-MIMO system to obtain optimal phase shift and beamforming matrix. A details description of the considered Systems and Channels Model, Deep Learning Structure, and Performance Metrics is given in Section 3.5.1, Section 3.5.2, and Section 3.5.3 respectively.

3.5.1 System and Channel Model

In this study, we have implemented a semi-passive Reconfigurable Intelligent Surface (RIS) architecture integrated with MIMO communication systems, utilizing a restricted number of Radio Frequency (RF) chains. Both the transmitting and receiving ends are outfitted with multiple antennas.

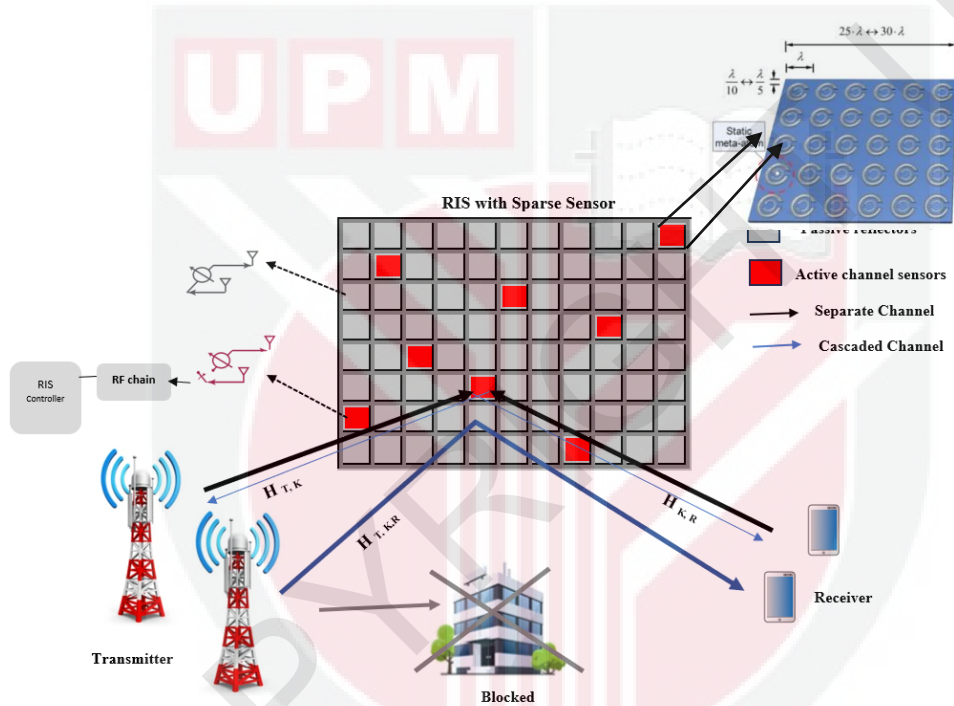


Figure 3.11: The proposed RIS-MIMO System for Uplink/Downlink Cascaded and Separate Channel Estimation

It's important to note that the terminology used in this study is based on the premise of (i) downlink communication, where the user equipment (UE) acts as the receiving entity, while the base station (BS) functions as the transmitting entity. (ii) Uplink and downlink, where the user equipment (UE) functions as the transmitter and receiver, and the base station (BS) serves as the transmitter and receiver. The system comprises two source nodes (S), each with N antennas, two destination nodes (D), each with M

antennas, and a single RIS consisting of K reflecting elements, which can be either active or passive.

The proposed RIS architecture, as shown in Figure 3.11, consists primarily of passive elements with a limited number of randomly placed active channel sensors. Only these active sensors are linked to the RIS controller's baseband. This architecture supports two operational modes: (a) receive mode, or channel sensing, where active elements connect to the baseband for channel estimation, and (b) reflection mode, where active and passive elements apply a phase shift to reflect incident signals. The RIS design relies on the relationship between meta-atoms and the wavelength of electromagnetic waves, which is crucial for optimizing how signals interact with the surface. Meta-atoms, the fundamental units of the RIS, are typically smaller than the wavelength to precisely control the phase, amplitude, and polarization of incoming waves. This sub-wavelength structuring allows for smooth wave manipulation, enhancing signal reflection and channel estimation accuracy. If the meta-atoms are larger or equal to the wavelength, their ability to control waves diminishes, leading to diffraction, scattering, and phase discontinuities that degrade performance. Thus, sub-wavelength meta-atoms are vital for ensuring precise wavefront control in RIS-MIMO systems, making this architecture particularly effective for advanced wireless communication. Meta-atoms are bounded within the square region of $[\lambda/5 - \lambda/10]$ as a rule of thumb [222].

Since a direct connection between S and D is impeded by substantial blockage or deep fading, we consider the channel efficiency between the n th antenna located at S and the k th element of the Reconfigurable Intelligent Surface (RIS) adheres to Rician fading, as outlined below[126]:

$$H_{T,K} = \sqrt{\frac{k_{k,n}}{k_{k,n}+1}} h_{k,n}^{(LOS)} + \sqrt{\frac{k_{k,n}}{k_{k,n}+1}} h_{k,n}^{(NLOS)}, \quad (3.13)$$

where $K_{k,n}$ represents the Rician factor for the respective link, and $h_{k,n}^{(LOS)}$ and $h_{k,n}^{(NLOS)}$, denote the line-of-sight (LoS) and non-line-of-sight (NLoS) components of the fading channel, respectively. The mathematical representation for the LoS component is provided in [126]:

$$h_{k,n}^{(LOS)} = \sqrt{\beta_0} e^{-j(k-1)\pi \sin \theta} d_{k,n}^{\frac{-\alpha}{2}}, \quad (3.14)$$

The variable θ indicates the angle of arrival at the RIS, while β_0 signifies the path loss observed at a one-meter reference distance. Regarding the Non-Line-of-Sight component, we have $h_{k,n}^{(NLOS)} = \tilde{h}_{k,n} d_{k,n}^{\frac{-\alpha}{2}}$ is modeled as a complex Gaussian random variable, with a zero mean and unit variance, representing small-scale fading. The channel between the k th RIS element and the m th antenna at destination D, denoted as $H_{K,R}$, is modeled similarly. The received signal at the destination is then expressed as

$$Y = H_{T,K} \Theta H_{K,R} x + n, \quad (3.15)$$

In this context, y is a matrix belonging to $C^{M \times I}$, $H_{T,K} \in C^{N \times K}$, channel matrix between S and RIS, $H_{K,R} \in C^{M \times K}$, channel matrix, representing the communication link between the RIS and destination D. Furthermore, n is an element of the $C^{M \times I}$ space, denoting the additive noise between the source node (S) and the RIS, and Θ represents the phase shift matrix at the RIS. The expression for Θ is as follows

$$\Theta = \text{diag}(a_1 e^{j\theta_1} \dots \dots, a_k e^{j\theta_k}), \quad (3.16)$$

The variable a_k represents the amplitude, and θ_k signifies the phase shift applied at the k th reflecting element. Although a_k is often treated as constant in numerous existing methods, it can also vary, as explored in [223] and [224]. In our approach, we employ discrete phase shifts with R-bit quantization, we employ discrete phase shifts with R-bit quantization, allowing each RIS element to have a 2^R distinct phase shift.

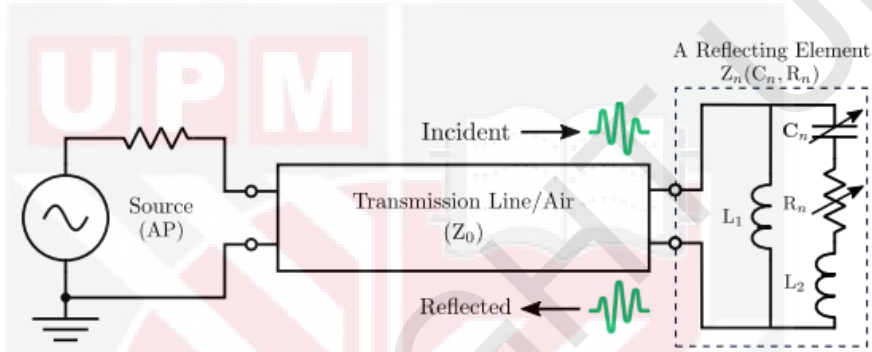


Figure 3.12: Transmission line model of a reflecting element [225]

The reconfigurability feature of RIS stems from the ability to independently adjust the reflection coefficient of each reflecting element (RE) using a specific control signal. The reflection coefficient, as a fundamental property, represents the fraction of a wave reflected as a result of impedance discrepancies in the medium. Let U_n represent the n th RE, and its reflection coefficient can be expressed as

$$v(n) = a(n)e^{j\theta(n)} \quad (3.17)$$

where $a(n)$ and $\theta(n)$ denote the adjustable amplitude and phase shift of U_n , respectively. Let $\tilde{E}(n)$ and $E(n)$ represent the incident and reflected electromagnetic

(EM) waves on U_n , respectively. According to its definition, the reflection coefficient $v(n)$ can be expressed as

$$v(n) = \frac{\tilde{E}(n)}{E(n)} \quad (3.18)$$

Furthermore, let Z_0 be the impedance of free space and $Z(n)$ the load impedance of U_n , the reflection coefficient $v(n)$ is therefore given by [226]

$$v(n) = \frac{Z(n) - Z_0}{Z(n) + Z_0} \quad (3.19)$$

Thus, the amplitude and phase of the reflection coefficient $v(n)$ can be expressed as

$$a(n) = \left| \frac{Z(n) - Z_0}{Z(n) + Z_0} \right| \quad (3.20)$$

and

$$\theta(n) = \arctan \left(\frac{\text{Im} \left(\frac{Z(n) - Z_0}{Z(n) + Z_0} \right)}{\text{Re} \left(\frac{Z(n) - Z_0}{Z(n) + Z_0} \right)} \right) \quad (3.21)$$

Most studies on RIS rely on an ideal model where phase shifts and amplitudes are adjustable independently. However, in practical implementations, hardware limitations often make this unattainable. In [121], an equivalent model for a reflecting element is analyzed to address these constraints. As depicted in Figure 3.12, the impedance of the n th element is influenced by the effective capacitance $C(n)$ and effective resistance $R(n)$, with L_1 , L_2 , $C(n)$, $R(n)$, and ω representing the bottom/inner layer inductance, top/outer layer inductance, effective capacitance, effective resistance, and angular frequency of the incident signal, respectively. The impedance can be expressed as a function of C_n and R_n by

$$Z_n(C_n, R_n) = \frac{j\omega L_1 (j\omega L_2 + \frac{1}{j\omega C_n} + R_n)}{j\omega L_1 + j\omega L_2 + \frac{1}{j\omega C_n} + R_n} \quad (3.22)$$

From equations (3.21) and (3.22), it can be seen that the amplitude and phase of the reflection coefficient can be adjusted by modifying $Z(n)$ through an external control signal. Specifically, from equation (3.22), $Z(n)$ is shown to depend on the effective resistance R_n and effective capacitance C_n , where R_n affects power loss due to device inefficiencies, and C_n accounts for charge accumulation in the semiconductor device. Various methods have been proposed for estimating channel H, which can be broadly divided into two main approaches: separate channel estimation (SCE) and cascaded channel estimation (CCE). In SCE, the BS-RIS and RIS-UE channels are estimated independently and then combined to reconstruct the cascaded channel. On the other hand, CCE estimates the entire cascaded channel directly using a specially designed channel estimation protocol. The stages of the system model for the uplink/downlink RIS-MIMO system are illustrated in Figure 3.13. The channels for both scenarios are modeled as described in Section 3.3.2, incorporating Rician fading characteristics.

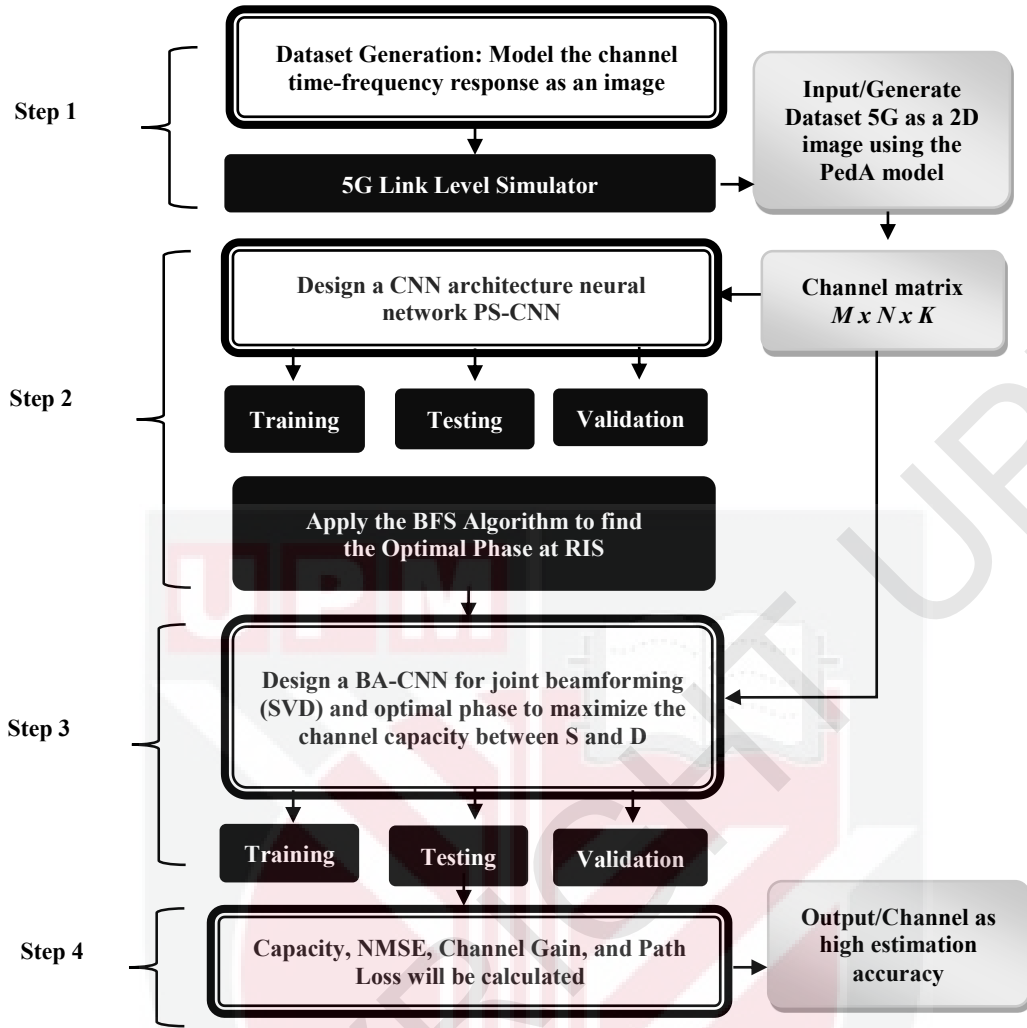


Figure 3.13: Methodology channel estimation solution for PSBA-H

The proposed methodology for PSBA-H as in Figure 3.13 performed at the UE for Cascaded Channel Estimation and at the sensing device in RIS for Separate Channel Estimation.

3.5.1.1 Cascaded Channel Estimation Scenario

In the cascaded channel estimation, the goal is to estimate the combined effect of both BS-RIS and RIS-UE channels, effectively treating them as one. In the context of a fully passive RIS without sensing capabilities, we consider the channels between the

BS and RIS, and the RIS and UE i.e., $H_{T,K}$ and $H_{K,R}$, cannot be independently estimated. Instead, only the combined, cascaded BS-RIS-UE channel can be estimated at the User Equipment (UE) in a downlink communication system. When the RIS is purely passive, the RIS has no baseband processing units. Therefore, no observations are available at the RIS, and the CE can only be performed either at the BS (in the uplink) or the UE (in the downlink). The CE estimation is performed at the UE in our scenario, as illustrated in Figure 3.15. In contrast to separate channel estimation, cascaded channel estimation applies to both Time Division Duplexing (TDD) and Frequency Division Duplexing (FDD) systems. Within TDD systems, the cascaded Channel State Information (CSI) can be estimated in a single direction and applied bidirectionally, leveraging uplink-downlink channel reciprocity. However, FDD systems necessitate supplementary feedback of the cascaded CSI for both uplink and downlink communication. Additionally, cascaded channel estimation offers increased practicality over separate channel estimation due to its substantially reduced hardware costs and energy consumption at the RIS, as it obviates the requirement for active sensing components. As depicted in Figure 3.14, we examine the downlink channel training scenario, where the Base Station (BS) transmits pilot signals, and the received signal at the User Equipment (UE) during time slot t is given by [126]:

$$y_{UE}^{(t)} = \sum_{k=1}^K \sqrt{P_{BS}} x_k^{(t)} \mathbf{H}_{T,K} \boldsymbol{\Theta}^{(t)} \mathbf{H}_{K,R} + \eta_{UE}^{(t)}, \quad (3.23)$$

In this context, $x_k^{(t)} \in \mathbb{C}^{M_{UX} \times 1}$ represents the pilot signal transmitted by the BS, $\boldsymbol{\Theta}^{(t)} = \text{diag}(\boldsymbol{\theta}^{(t)})$ denotes the diagonal reflection matrix of RIS during time slot t , and $\eta_u^{(t)} \in \mathbb{C}^{M_{UX} \times 1}$ is the Additive White Gaussian Noise (AWGN) vector at the User Equipment (UE). Based on the properties of the Khatri-Rao product, we can derive

$$\text{vec}(\mathbf{H}_{T,K} \boldsymbol{\theta}^{(t)} \mathbf{H}_{K,R}) = \mathbf{H}_{k,R}^T \odot \mathbf{H}_{T,K} \boldsymbol{\theta}^{(t)}, \quad k = 1, \dots, K, \quad (3.24)$$

$$\overrightarrow{\mathbf{H}_k}$$

where $\overrightarrow{\mathbf{H}_k} \in \mathbb{C}^{M_B M_u \times N}$ is the cascaded channel for user k , $\text{vec}(\cdot)$ indicates the vectorization operation, and $\odot$ represents the Khatri-Rao product. Additionally, using the Kronecker product allows us to write equation (3.23) more compactly as

$$y_{UE}^{(t)} = \sum_{k=1}^K \sqrt{P_{BS}} \left(\left(x_k^{(t)} \otimes \mathbf{I}_{M_{UE}} \right) \right) \overrightarrow{\mathbf{H}_k} \boldsymbol{\theta}^{(t)} + \eta_{UE}^{(t)}, \quad (3.25)$$

where $\otimes$ stands for the Kronecker product. From (3.24) and (3.25), we can observe that due to the cascade of the BS-RIS and RIS-UE channels, the number of channel coefficients to be estimated in the cascaded channels $\{\overrightarrow{\mathbf{H}_k}\}_{k=1}^K$ is generally larger than that in the separate channels $\mathbf{H}_{T,K}$ and $\overrightarrow{\mathbf{H}_k}\}_{k=1}^K$ typically results in increased training overhead and poses new practical challenges.

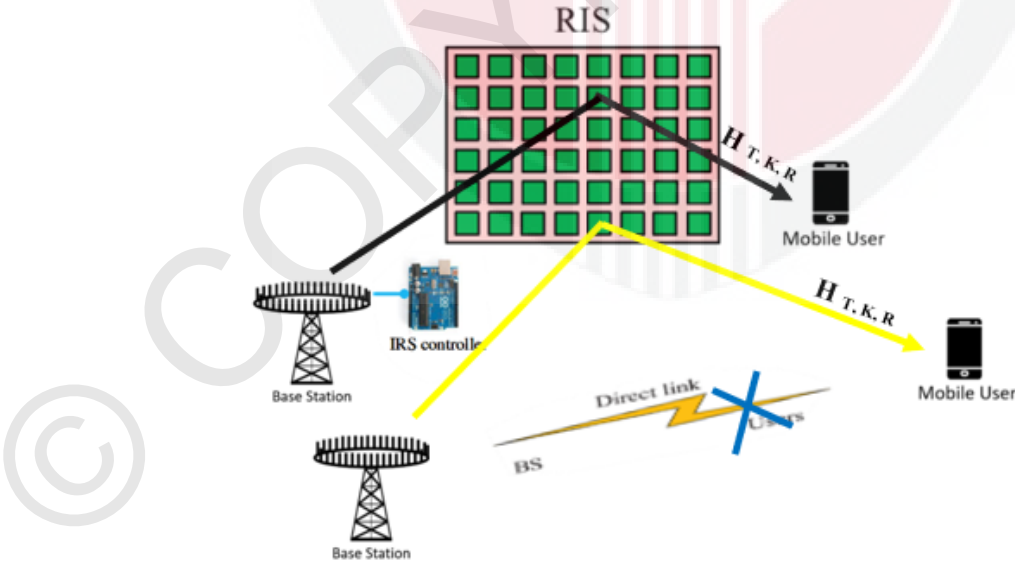


Figure 3.14: Scenario 1 (Downlink) Communication System for Cascaded Channel

Downlink Pilot Transmission Protocol: Transmit known signals (pilot sequences) from the transmitter (BS). The signals are reflected at the RIS fully passive elements and combined at the receiver (UE). The receiver estimates the cascaded channel and sends the estimates to the RIS and BS for the design of the RIS phase control matrix and beamformer at BS. This procedure leads to angle estimation, i.e., AoDs at the BS and AoAs at the UE. Maximize the channel capacity (high data rate) by reducing the loss between BS and UE.



Figure 3.15: Downlink Cascaded Channel Estimation performance at the receiver

Cascaded channel estimation is particularly applicable in scenarios where the combined influence of the Base Station (BS), Reconfigurable Intelligent Surface (RIS), and User Equipment (UE) needs to be captured as a single entity. Here are key situations when cascaded channel estimation is utilized:

1. **Fully Passive RIS:** With a fully passive RIS that lacks dedicated sensing devices, independent estimation of the BS-RIS and RIS-UE channels is impractical. Consequently, the only estimable channel is the combined BS-RIS-UE channel, typically at one end of the communication link, either the UE for downlink or the BS for uplink.
2. **Simplified Implementation:** Cascaded channel estimation can simplify the estimation process since it reduces the number of parameters that need to be estimated compared to separate channel estimation methods. This is particularly beneficial in systems with a large number of antennas or RIS elements, where managing individual channel estimates may become cumbersome.

3. **Optimization of Phase Shifts:** When optimizing the phase shifts of RIS elements, cascaded channel estimation is necessary to determine how these adjustments affect the overall system performance. This method allows for simultaneous optimization of beamforming and phase corrections based on the combined channel characteristics.
4. **Low Pilot Overhead:** In scenarios where minimizing pilot overhead is critical, cascaded channel estimation can be advantageous. By estimating the combined channel, fewer pilot signals may be required compared to estimating each link separately, thus reducing the overall signaling burden on the system.

When a fully passive RIS is used to estimate the cascaded BS-RIS-UE channel, and in order to jointly determine the beamforming at the Base Station (BS) and the phase shift at the RIS, the received signal at the User Equipment (UE) is expressed as [126]

$$Y_{UE} = \mathbf{F}\boldsymbol{\phi}\mathbf{1}_F x + \boldsymbol{\eta} \quad (3.26)$$

Where $\boldsymbol{\phi} = \text{diag}(\phi_v, \dots, \phi_v) \in \mathbb{C}^{NK \times NK}$, $\mathbf{1}_F = [\mathbf{1}_1^T, \dots, \mathbf{1}_1^T]$, $\mathbf{1}_n$ is the K -by N matrix with the elements of the n th column being ones and all other elements being zeros. Letting $Q = \min(M, N)$, the beamforming at BS can be obtained as

$$x = \mathbf{W}s, \quad (3.27)$$

Where $\mathbf{W} = [\mathbf{w}_1, \dots, \mathbf{w}_Q]$, $\mathbf{w}_q$ is the q -th beamforming vector, $s = [s_1, \dots, s_Q]^T$, s_q is the q -th transmit data, and we assume $E[s_q^2] = 1$ for all q . Substituting (3.26) into (3.27) gives

$$Y_{UE} = \mathbf{F}\boldsymbol{\phi}\mathbf{1}_F \mathbf{W}s + \boldsymbol{\eta}, \quad (3.28)$$

The joint beamforming and phase shift are to maximize the channel capacity between S and D as [126]

$$\max_{\mathbf{W}, \phi_v} C = \log \det \left| \mathbf{I} + \frac{\mathbf{A} \mathbf{W} \mathbf{W}^H \mathbf{A}^H}{\sigma^2} \right|, \quad (3.29)$$

Where $\mathbf{A} = \mathbf{F} \phi \mathbf{1}_F \in \mathbb{C}^{M \times N}$

The formula for the singular value decomposition of $\mathbf{A}$ is $\mathbf{A} = \mathbf{U} \mathbf{\Lambda} \mathbf{V}^H$, to calculate the AoD and AoA, where $\mathbf{U} \in \mathbb{C}^{M \times M}$ and $\mathbf{V} \in \mathbb{C}^{N \times N}$ are complex matrix of right singular vectors and left singular vectors, respectively, and $\mathbf{\Lambda} \in \mathbb{C}^{M \times N}$ is complex singular value matrix. Given a specific value for ϕ_v , the optimal beamforming vectors are defined as

$$\mathbf{w}_q = \sqrt{P_q} \mathbf{v}_q, \quad q = 1, 2, \dots, Q, \quad (3.30)$$

Where $\mathbf{v}_q$ is the q -th right singular vector in $\mathbf{V}$, P_q is the power allocated for the q -th transmit data, which is obtained through water-filling to satisfy the transmit power constraint, $\sum_{q=1}^Q P_q \leq P_s$. Substituting (3.30) and (3.31) gives

$$\max_{\mathbf{P}} C = \log \det \left| \mathbf{I} + \frac{\mathbf{P} \mathbf{\Lambda} \mathbf{\Lambda}^H}{\sigma^2} \right|, \quad (3.31)$$

Where $\mathbf{P} = \text{diag}[P_1, \dots, P_Q, \underbrace{0, \dots, 0}_{M-Q}]$.

The cascaded network's training objective is to maximize system capacity, which is the same as minimizing the negative of its outputs, as described in [126]

$$\min \{ \sum_{l=1}^L (C^{(l)} - C_{F(l), \phi(l)})^2 \} \quad (3.32)$$

3.5.1.2 Separated Channel Estimation Scenario

Consider the system setup shown in Figure 3.16: an RIS with K reconfigurable elements aids communication between a multi-antenna BS and a multi-antenna UE. (The BS or UE can serve as a transmitter/receiver). This multi-antenna assumption is principally made to facilitate a clearer explanation of the concepts and proposed methods. The formal communication framework is OFDM-based, utilizing 72 subcarriers. We will now analyze the system performance for the k th subcarrier. Let $H_{T,K}$ denote the downlink channel matrix from the transmitter to the RIS, and let $H_{K,R}$ denote the uplink channel matrix from the receiver to the RIS, both considered at the k th subcarrier. Assuming channel reciprocity, the channel matrix from the RIS to the receiver is then given by $H_{T,K}^T$, and $H_{K,R}^T$ the channel matrix from the RIS to the transmitter.

Conversely, the separate channel estimation method involves independently estimating the transmitter to RIS (BS-RIS) and RIS to Receiver (RIS-UE) channels. In the case of a semi-passive or hybrid RIS that includes N_s dedicated sensing devices, these channels can be estimated separately at those sensing devices using pilot signals transmitted from the BS/UE, as illustrated in Figure 3.16. Initially, during the downlink phase, the BS transmits pilot signals to the semi-passive RIS. The RIS's passive elements remain inactive at this stage. Its active elements, however, receive these pilots, estimate the BS-RIS channel, and then send these estimation results back to the BS to enable efficient data transmission. Next, the RIS estimates the UE-RIS channel using the uplink pilot signals sent by the UE. Once its semi-passive elements are activated, the RIS completes this channel estimation process and then forwards the

resulting information to the UE. Channel estimation takes place at the RIS in this scenario, allowing the BS-RIS and UE-RIS channels to be estimated separately. Generally, determining these individual channels is significantly less complex than estimating the complete BS-UE-RIS cascaded channel, thereby reducing the overall pilot overhead over an extended period. This methodology functions efficiently in TDD systems by using channel reciprocity to determine the reverse CSI from the RIS to the BS/UE. However, in FDD systems, it requires active sensors on the RIS for both transmission and reception, increasing hardware costs and power consumption. To reduce costs and energy consumption, we utilize only a few affordable sensing devices, typically featuring low-resolution analog-to-digital converters (ADCs), which may be incorporated into the semi-passive RIS. Specifically, referring to Figure 3.16, we let $\tilde{\mathbf{G}}(\mathbf{H}_{T,K}) \in \mathbb{C}^{N_s \times M_B}$ and $\tilde{\mathbf{H}}(\mathbf{H}_{K,R}) \in \mathbb{C}^{N_s \times N_U}$ denote the channels from the BS and UE to the N_s sensing devices, respectively. Moreover, let $\mathbf{X}_B \in \mathbb{C}^{M_B \times T}$ and $\mathbf{X}_U \in \mathbb{C}^{N_U \times T}$ represent the pilot sequences transmitted by the BS and UE, respectively, where T is the number of pilot symbols in the channel sensing period. Following the methodology outlined in [227] (“a survey on channel estimation for RIS-aided communications”), the signal received at the N_s sensing devices is expressed by [227]

$$\mathbf{Y}_S = \mathbb{Q}(\sqrt{P_B} \tilde{\mathbf{G}} \mathbf{X}_B + \sum_{K=1}^K \sqrt{P_U} \tilde{\mathbf{H}}_K \mathbf{X}_U + \boldsymbol{\eta}_S), \quad (3.33)$$

where $\mathbb{Q}(\cdot)$ denotes the quantization function determined by the ADC resolution, P_B and P_U represent the transmit power at the BS and UE, respectively, and $\boldsymbol{\eta}_S \in \mathbb{C}^{N_s \times T}$ is the additive white Gaussian noise affecting the sensing devices. Consequently, the central challenge for this separate channel estimation approach at the RIS is how to accurately reconstruct the Channel State Information (CSI) between the BS/UE and the individual RIS reflecting elements, relying solely on the signal measurements

specified in (3.33) which are obtained from a limited number of low-cost sensing devices. Consequently, there is a need for efficient signal processing techniques to interpolate or extrapolate the limited measurement data available in Y_s , enabling the construction of the complete CSI between the BS/UE and the RIS reflecting elements, i.e., $H_{T,K}$ and $\{H_{K,R}\}_{K=1}^K$. More efficient channel estimation can be achieved by leveraging common channel characteristics like low rank, sparsity, and spatial correlation, which are particularly prominent in mmWave [228] and THz [229] frequency bands. However, further research is required in channel modeling and estimation to enhance CSI reconstruction accuracy by addressing distortions caused by factors like quantization errors, ambient noise, and circuit non-linearity. In this configuration, the RIS contains K passive elements equipped with RF phase shifters, lacking direct baseband connections. Additionally, K active sensors are selected from the RIS elements. These active sensors, as shown in Figure 3.16, are designed for dual operation: (i) a channel sensing mode where they function as receivers with full RF chains and baseband processing, and (ii) a reflection mode where they behave identically to the passive elements, reflecting the incident signal.

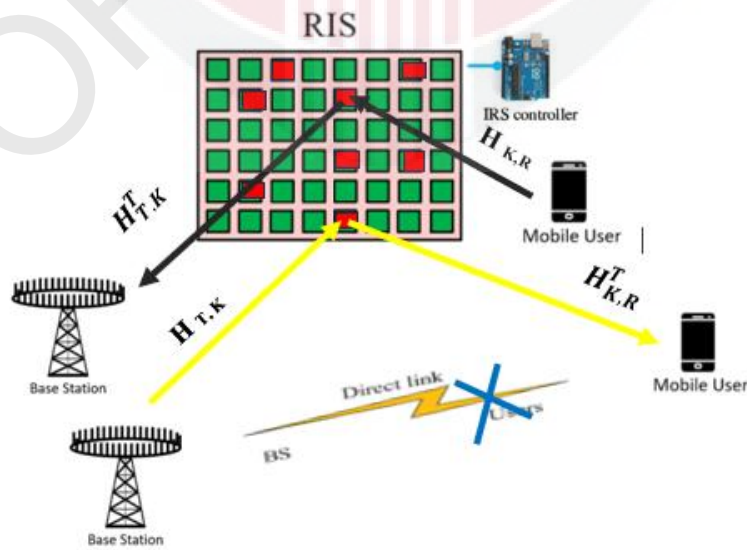


Figure 3.16: Scenario 2(uplink/downlink) Communication System for Separate Channel

1-Downlink Pilot Transmission Protocol: Transmit known signals (pilot signal) from the transmitter (BS) to the N_s sensing device at RIS. During sensing mode, all semi-passive elements are active, while the purely passive components are turned off. In this state, signals impinging on the RIS are received by these active elements (sensing devices) instead of being reflected. This received signal is then used for channel estimation. The RIS provides feedback to the BS about the estimation for the design of beamformers. The BS transmits the data signal to RIS after turning off the sensing element and turning on the reflected element to reflect the signal toward the UE. Maximize the channel capacity between BS and UE.

2-Uplink Pilot Transmission Protocol: Transmit known signals (pilot signal) from the transmitter (UE) to the N_s sensing device at RIS. During sensing mode, all semi-passive elements are active, and the other passive components are deactivated. The signals are received at the RIS (sensing devices) instead of reflecting, and then the channel will be estimated at these sensing devices. The RIS provides feedback to the UE about the estimation for the design of beamformers. The UE transmits the data signal to RIS after turning off the sensing element and turning on the reflected element to reflect the signal toward the BS. Maximize the channel capacity between UE and BS.

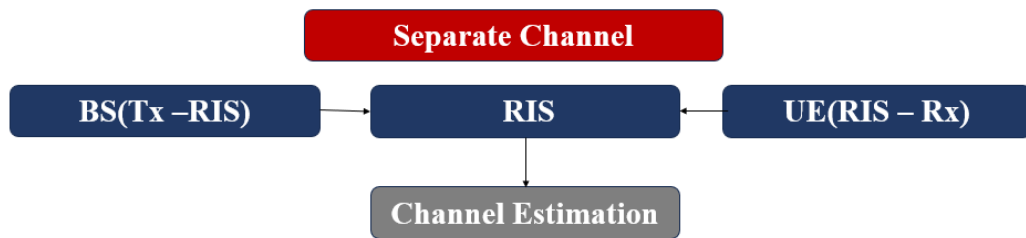


Figure 3.17: Separate channel estimation performance at the RIS

The separate channel estimation scenario in RIS-MIMO systems occurs under specific conditions that facilitate the independent estimation of the channels between the Base Station (BS) and the Reconfigurable Intelligent Surface (RIS), as well as between the RIS and the User Equipment (UE). Here are key situations where this approach is applicable:

1. **Presence of Dedicated Sensing Devices:** Separate channel estimation is particularly feasible when the RIS is equipped with dedicated sensing devices or active elements that can analyze incoming signals. These devices can transmit dedicated pilot signals to estimate the individual channels independently, allowing for more precise measurements of both the BS-RIS and RIS-UE channels.
2. **Semi-Passive or Hybrid RIS Configurations:** In scenarios where the RIS operates in a semi-passive or hybrid mode, it can utilize active components to assist in channel estimation. This setup enables the RIS to perform independent measurements of its channels, facilitating separate channel estimation.
3. **Quasi-Static and Time-Varying Channel Information Requirements:** Separate channel estimation is beneficial when detailed information about each channel segment (BS-RIS and RIS-UE) is essential. Under quasi-static conditions, where the channel remains stable over time, separate estimation provides high-resolution channel data with manageable pilot overhead, facilitating optimized BS-RIS configuration. In contrast, during time-varying conditions, separate estimation enables frequent updates to the RIS-UE channel, improving signal quality and adaptability in dynamic environments, albeit with increased pilot overhead.
4. **Different frequencies:** When the BS and UE operate at different frequencies or under different conditions that do not significantly affect each other, it may be practical to estimate their respective channels separately without significant loss of accuracy.

When employing a semi-passive RIS, the separate BS-RIS and RIS-UE channels $H_{T,K}$, and $H_{K,R}$ can be estimated independently. In this section, we present the design of the phase control matrix at the RIS and the beamforming vectors at the BS and UE. The received signal at the RIS (N_s sensing device) is given by [227]:

$$Y_{N_s} = \mathbf{y}_{BS} + \mathbf{y}_{UE} \quad (3.34)$$

$$y_{RIS}^{(t)} = \sum_{k=1}^K \sqrt{P_{BS}} \mathbf{H}_{T,K} \boldsymbol{\theta}^{(t)} x_k^{(t)} + \eta_s^{(t)} \quad (3.35)$$

$$y_{RIS}^{(t)} = \sum_{k=1}^K \sqrt{P_{UE}} \mathbf{H}_{K,R} \boldsymbol{\theta}^{(t)} x_k^{(t)} + \eta_s^{(t)} \quad (3.36)$$

Where $\phi = \text{diag}(\phi_v, \dots, \phi_v) \in \mathbb{C}^{MKN \times MKN}$, let $\mathbf{x}_{BS}$ and $\mathbf{x}_{UE}$ represent the pilot sequences transmitted by the BS and UE, respectively. Let T be the number of pilot symbols within the channel sensing period. Using these definitions, the beamforming at the sensing device, N_s , can be obtained as:

$$\mathbf{x}_{N_s} = \mathbf{x}_{BS} + \mathbf{x}_{UE} \quad (3.37)$$

$$\mathbf{x} = \mathbf{W}\mathbf{s}, \quad (3.38)$$

Where $\mathbf{W}$ represents the q -th beamforming vector, s is the q -th transmit data symbol. The objective is to jointly optimize the beamforming (represented by vectors like $\mathbf{W}$) and the RIS phase shifts to maximize the channel capacity between S and D [227]

$$\max_{\mathbf{W}, \phi_v} C \frac{1}{K} \sum_{k=1}^K \log_2 (1 + \text{SNR} |(h_{T,K} \odot h_{K,R})^T \phi|^2) \quad (3.39)$$

We define $H_{T,K}$ and $H_{K,R}$ uplink/downlink channels from the transmitter and receiver to the RIS at the k th subcarrier, and by reciprocity, $H_{T,K}^T, H_{K,R}^T$ as the uplink/downlink channels from RIS to the transmitter and receiver then we can write the received signal to the UE as $\mathbf{H}_{k,R}^T$ in the case of the downlink and at the BS as $\mathbf{H}_{T,K}^T$ in the case of the uplink

$$y_{UE} = \mathbf{H}_{k,R}^T \odot \mathbf{H}_{T,K} x_k + \eta_k \quad (3.40)$$

$$y_{BS} = \mathbf{H}_{T,K}^T \odot \mathbf{H}_{K,R} x_k + \eta_k \quad (3.41)$$

3.5.2 Deep Learning Structure and Training

This section proposes a new deep learning-based approach to tackle the third problem directly. The proposed approach obtains a solution in only two steps by the neural network, namely, predicting the optimal phase shifts from optimal effective channel matrix H based on channels $H_{T,K}$ and $H_{K,R}$ and predict beamforming based on the channel matrix H in the RIS-MIMO system, we propose a learning model composed of two convolutional neural networks, Net1 and Net2, as illustrated in Figure 3.18. After training Net1 (PS-CNN), we employ a brute force search (BFS) algorithm to obtain optimal phase shifts, and before training Net2 (BA-CNN), we calculate the initial beamforming vectors using the Singular Value Decomposition (SVD) algorithm. The system's inputs consist of an $N \times M \times K$ channel matrix H , where each entry is represented by a cascaded group of $K 2^R$ - dimensional category vectors. Every group relates to the R -bit discrete phase shift applied to a single RIS element. To exploit the inherent structural relationship between the antenna-side and user-side channels, rather than treating them separately, we used this model to construct features for each reflecting element. Specifically, the feature matrix for the K element is $F = H_{T,K} \times H_{K,R} \in \mathbb{C}^{N \times M}$. Besides, the real and imaginary parts need to be separated into two features, so there are a total of $2(N \times K \times M)$ features per data, which capture the channel state information between the source, RIS, and destination.

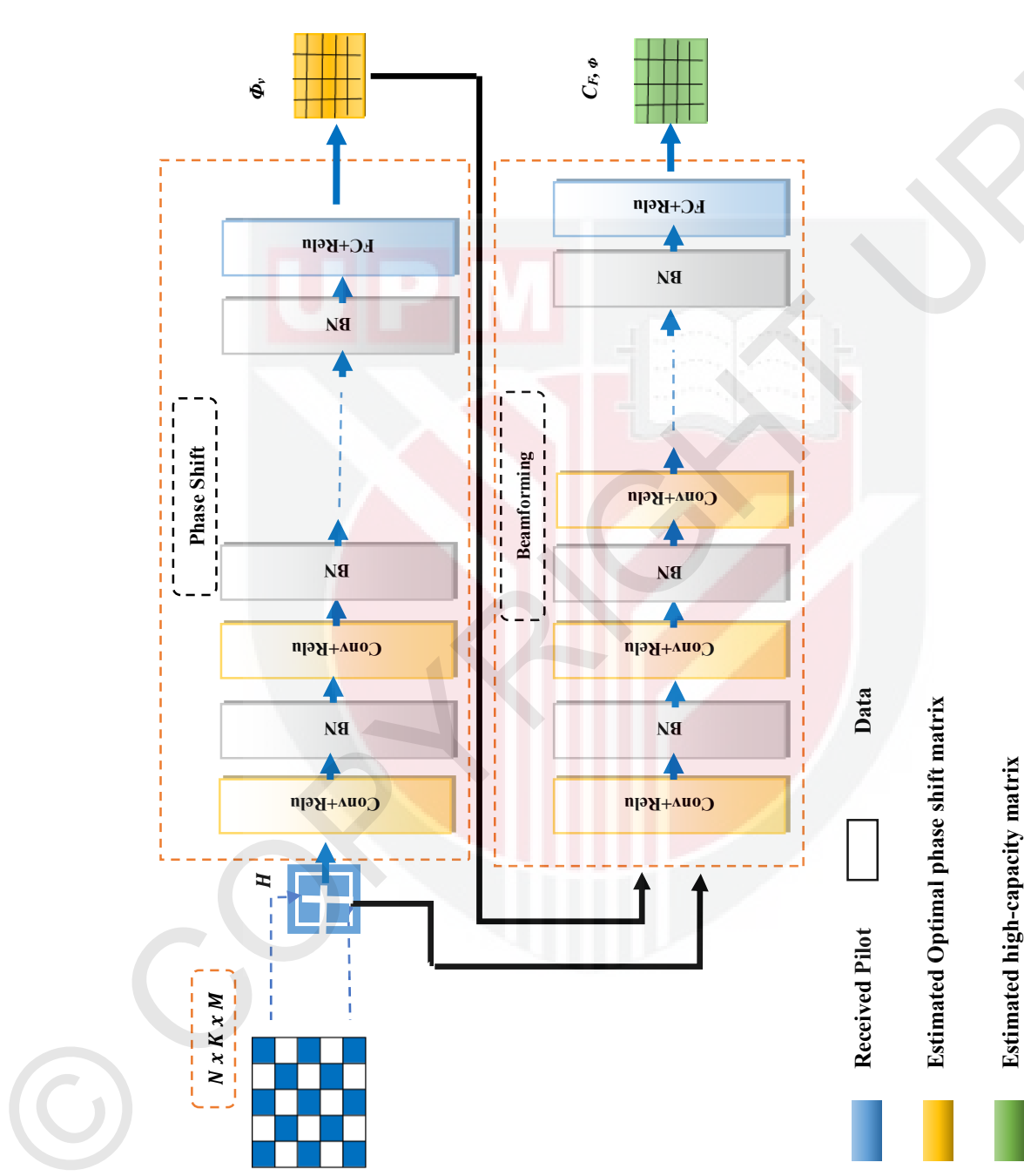


Figure 3.18: Two-Stage PSBA-CNN network architecture

3.5.2.1 Optimal Phase Shift Estimation Network

The primary objective of the Phase Shift Estimation Network is to derive the optimal phase shift values based on the channel matrix and RIS element information. Net1, designed for optimal phase shift estimation, employs a brute force search (BFS) algorithm to systematically evaluate all possible configurations of phase shifts for the RIS elements. The input to Net1 is a 2D image representation of the channel matrix H , which captures the channel state information between the source, RIS, and destination. Given that each RIS element can have multiple discrete phase shift values determined by R -bit quantization, the total number of combinations is 2^{KR} , where K is the number of RIS elements. We design a Net1 with three convolutional layers with $64 \times 4 \times 4$ kernels each, followed by one fully connected layer with 128 neurons. A batch normalization (BN) layer is inserted between each two layers to prevent overfitting and promote efficient training. Previous layers utilize the rectified linear unit (ReLU) activation function, whereas the final layer, which predicts Φ_v , employs a linear activation. Considering the nature of phase shifts, the Tanh activation function is appropriate, especially given that phase shift values are range of $-\pi$ to π . After training Net1, we add the Brute Force Search algorithm after the fully connected layer of the Phase Shift Network, where the network output is the Initial Phase Shift Prediction Φ_v . The BFS will refine the output from the network and ensure optimal phase shift selection based on the objective function.

3.5.2.2 Beamforming Optimization Network

The Net2 Optimization Network aims to predict the high-capacity data rate by processing the optimal phase shifts from the prior network and the channel matrix H . It is specifically intended for beamforming calculations through Singular Value Decomposition (SVD). Net2's input consists of the channel matrix H and the optimal phase shift vector Φ_v , obtained from Net1. From these, it computes the equivalent channel matrix, which represents the integration of phase shifts and beamforming vectors. To derive the singular values and vectors, the SVD of the equivalent channel matrix is performed, represented as $A = U\Lambda V$, where $U \in C^{M \times M}$ and $V \in C^{N \times N}$ are complex matrices of left and right singular vectors, respectively, and $\Lambda \in C^{M \times N}$ is a complex matrix holding the singular values. Based on the SVD results, optimal beamforming vectors are calculated using: $w_q = \sqrt{P_q} v_q$, $q=1,2,\dots, Q$, where v_q represents the q -th right singular vector in V , and P_q is determined through water-filling to satisfy transmit power constraints. The SVD calculates the AoA and AoD matrices initially, then is input to Net2 to effectively predict the optimal AoA and AoD from the equivalent channel matrix A . The left singular vector U represents the AoA at the destination, while the right singular vector V represents the AoD at the source. By selecting the appropriate singular vectors corresponding to the strongest singular values, Net2 can determine the optimal beamforming vectors that maximize the channel capacity between the source and destination. This structured approach allows Net2 to effectively optimize beamforming based on the phase shifts estimated in Net1, ultimately enhancing system capacity in RIS-MIMO networks. We adopt another neural network for transmitting beamforming. The input of Net2 is the effective channel computed based on the predicted phase of Net1 and the channel matrix H . We

design a Net2 with four convolutional layers with $64 \times 3 \times 3$ kernels each, followed by two fully-connected layers with 128 neurons. The usage of normalization, BN layer, and activation function is similar to Net1. In the end, high capacity is obtained according to equation (3.39). Given the regression-based prediction task, the Mean Squared Error (MSE) loss function is chosen as the performance evaluation metric, as defined in equation (3.32). Before training Net2, the Singular Value Decomposition (SVD) is placed before the Beamforming Network to extract essential channel characteristics, such as the Angle of Arrival (AoA), Angle of Departure (AoD), and channel gains. This placement is justified because SVD efficiently decomposes the high-dimensional channel matrix into its most important components, allowing the network to focus on the dominant communication paths. By applying SVD at this stage, we reduce the input complexity by isolating the significant spatial directions (AoA, AoD) and the strongest communication paths (through the singular values). This not only helps in dimensionality reduction, making it easier for the subsequent Beamforming Network to optimize beamforming but also ensures that the network operates on inputs that are physically interpretable and highly relevant to the beamforming task. Additionally, SVD provides near-optimal beamforming directions under ideal conditions, which can be further fine-tuned by the Beamforming Network to account for real-world imperfections like noisy or incomplete channel state information. This strategic positioning allows the network to perform beamforming optimization more efficiently and robustly. Initially, Net2 is trained to minimize the loss function specified in (3.32). Following this training, Net2 is connected in series (cascaded) with Net1, as depicted in Figure 3.18. The resulting combined network is then trained with the objective of maximizing system capacity. Net2 takes F and Φv as inputs and outputs the corresponding capacity C_F, ϕ . For network training, we

choose the Adam optimizer to update weights and set the initial learning rate to 0.001, and the batch size is 128. Therefore, for sufficient training and accurate evaluation of the model, we generated 30,000 samples for the training set, 5,000 for the validation set, and 5,000 for the testing set. Besides, early stopping with patience 20 is deployed to prevent overfitting and obtain the model with the best validation performance.

Algorithm 2: Train the Net1 and Net2 for Cascaded Channel Estimation

Procedure:

1. Generate the dataset by scenario 1, from $N \times K \times M$, then obtain the least square channel matrix $H_{T,K,R}$ (BS-RIS-UE) and the random phase shift matrix ϕ_v .

2. Train Network 1

Input: 40,000 frames channel matrix $H_{LS(T,K,R)}$, true phase shift ϕ_{True} , and random phase shift

ϕ_v .
 $i = 0$ (initial epoch)

Initialize optimizer = Gradient Descent

While $i < 400$ (max epochs)

- From F and ϕ compute the equivalent channel matrix $A = F \text{diag}(\phi_1, \dots, \phi_v) \mathbf{1}_F$
- Obtain optimal phase control matrix ϕ_v

$i = i + 1$

End While

Return ϕ

Output: ϕ_v (Estimated optimal phase shifts)

3. Cascaded Net1 with Net2 after train Net1

4. Train Network 2

Input: 40,000 frames channel matrix $H_{LS(T,K,R)}$, optimal phase shift matrix.

$i = 0$ (initial epoch)

Initialize optimizer = Adam

Initialize loss function = MSE

While $i < 400$ (max epochs)

- From F and ϕ compute the equivalent channel matrix $A = F \text{diag}(\phi_1, \dots, \phi_v)$
- Apply the water-filling to obtain the transmit power P
- Obtain the capacity as $\max_{W, \phi_v} C = \log \det \left| I + \frac{A W W^H A^H}{\sigma^2} \right|$, (3.31)

Where $A = F \phi \mathbf{1}_F \in \mathbb{C}^{M \times N}$

- Calculate the loss function as $\min \{ \sum_{l=1}^L (C^{(l)} - C_{F(l), \phi(l)})^2 \}$ (3.32)

$i = i + 1$

End While

Return C

Output: $C_{F, \phi}$ (corresponding capacity)

End Procedure

In Algorithm 2, which is for the cascaded scenario, Net1 receives a random phase matrix as input and outputs the optimal phase for each RIS element. This output is then

fed into Net2. Similarly, in Algorithm 3, which is for a separate scenario, Net1 also receives a random phase matrix as input to determine the optimal phase values for the RIS elements, and the result is passed to Net2. Essentially, in both algorithms, the random phase matrix is used as the initial input to Net1, and the optimal phase output from Net1 is then processed by Net2.

Algorithm 3: Train the Net1 and Net2 for Separate Channel Estimation

Procedure:

1. Generate the dataset by scenario 2, from $M \times K \times N$, then obtain the least square channel matrix $H_{T,K}$ and $H_{K,R}$ (BS-RIS, RIS-UE), and the random phase shift control matrix ϕ_v .

2. Train Network 1

Input: 80,000 frames channel matrix H_{LS} , true phase shift ϕ_{True} , and random phase shift ϕ_v .
RIS receives two orthogonal pilot signals from the transmitter and receiver, and the active elements of the RIS will receive these pilots and estimate the sampled channel vectors $h(s)$.

$i = 0$ (initial epoch)

Initialize optimizer = Gradient Descent

While $i < 400$ (max epochs)

- From F and ϕ compute the equivalent channel matrix $A = F \text{diag}(\phi_1, \dots, \phi_v) 1_F$
- Obtain optimal phase control matrix ϕ_v

$i = i + 1$

End While

Return ϕ

Output: ϕ_v (Estimated optimal phase shifts)

3. Cascaded Net1 with Net2 after train Net1

4. Train Network 2

Input: 80,000 frames channel matrix H_{LS} , optimal phase shift matrix ϕ_v .

$i = 0$ (initial epoch)

Initialize optimizer = Adam

Initialize loss function = MSE

While $i < 400$ (max epochs)

- From F and ϕ compute the equivalent channel matrix $A = F \text{diag}(\phi_1, \dots, \phi_v)$
- Calculate the transmit power P by applying water-filling
- Obtain the capacity as

$$\max_{W, \phi_v} C \frac{1}{K} \sum_{k=1}^K \log_2 (1 + \text{SNR} |(h_{T,K} \odot h_{K,R})^T \phi|^2) \quad (3.32)$$

- Calculate the loss function as $\min\{\sum_{l=1}^L (C^{(l)} - C_{F(l), \phi(l)})^2\}$ (3.39)

$i = i + 1$

End While

Return C

Output: $C_{F, \phi}$ (corresponding capacity)

End Procedure

3.5.3 Performance Metrics

This section outlines the performance evaluation metrics used, precisely Data rate, Capacity, Path loss, Pilot overhead, Total Channel Gain, Normalized Mean Square Error(NMSE), and Time Complexity. Understanding how these metrics interact with various parameters such as signal-to-noise ratio (SNR), observation angle, number of RIS elements, and total channel gain provides valuable insights into optimizing RIS-MIMO configurations.

3.5.3.1 Capacity vs. SNR

The data rate R in a RIS-MIMO system can be expressed using the Shannon capacity formula: [230,231]

$$R = \log_2(1 + \text{SNR} \cdot \det(H^H H)), \quad (3.42)$$

where H is the channel matrix, and SNR is the signal-to-noise ratio. Analyzing capacity against SNR is crucial for understanding the maximum achievable throughput under different noise conditions. Higher SNR typically leads to increased data rates and capacity, allowing for more efficient use of bandwidth.

3.5.3.2 Normalized Path Loss vs. Observation Angle

Path loss $L(d)$ in RIS-MIMO communications is critical for understanding signal degradation over distance. A general formula for free-space path loss can be expressed as[232]:

$$L(d) = 20 \log_{10}(d) + 20 \log_{10}(f) + K , \quad (3.43)$$

Where d is the distance between the transmitter and receiver, f is the frequency of operation, and K is a constant that accounts for system losses. The observation angle significantly affects normalized path loss in RIS-MIMO systems, as the orientation and positioning of the RIS elements can optimize signal reflection and minimize losses. Understanding the relationship between normalized path loss and observation angle is crucial for optimizing RIS placement and configuration.

3.5.3.3 NMSE vs. Number of RIS Elements

NMSE is a pivotal metric for evaluating channel estimation performance. It is defined as [231,233]:

$$NMSE = \frac{\mathbb{E}[\|H - \hat{H}\|^2]}{\mathbb{E}\|H\|^2} \quad (3.44)$$

where H is the true channel matrix and $\hat{H}$ is the estimated channel matrix. As the number of RIS elements increases, the potential for improved channel estimation accuracy also rises, leading to lower NMSE values and better overall system performance.

3.5.3.4 Total Channel Gain

Total channel gain (G_{total}) can be expressed as [234]:

$$G_{total} = \frac{A}{4\pi H_{T,K}} \cdot \frac{A}{4\pi H_{K,R}} \quad (3.45)$$

An increase in this distance leads to higher path loss, reducing the G_{total} . The effective gain can be influenced by factors like antenna configurations and frequency of operation.

3.5.3.5 Pilot Overhead

Pilot overhead refers to the additional resources, typically in the form of time slots or symbols, allocated for transmitting pilot signals in wireless communication systems. These pilot signals are essential for channel estimation, allowing receivers to obtain information about the channel conditions. Pilot overhead is typically expressed as a percentage or ratio of the total resources allocated to pilots. In wireless communication, the transmitted signal can be distorted by various factors, such as Multipath fading when signals take multiple paths to reach the receiver. Doppler shift due to the relative movement between the transmitter and receiver. Noise from the environment and electronic components. The pilot overhead can be calculated as:

$$Pilot\ Overhead(\%) = \frac{N_{Pilot}}{N_{Total}} \times 100\ \% \quad (3.46)$$

Where: is the number of resources (symbols or subcarriers) used for pilots. N_{Total} is the total number of resources available (pilots + data).

3.5.3.6 Time Complexity

Time complexity measures the total amount of time taken to execute all statements of the algorithm or to execute, as a function of the length of input data. It should be as small as possible because the more time our algorithm takes, will increase the cost of it. The time complexity of any model is dependent on the number of operations, input/Output dataset dimensions, and several parameters. To make a model faster and less complex should use fewer layers, efficient algorithms, CPU, and GPU Parallelization.

3.6 Summary

This chapter explores two scenarios of channel estimation in RIS-MIMO systems, focusing on optimizing phase shifts and beamforming to maximize the received signal-to-noise ratio. It details the mechanisms of RIS-MIMO wireless communication and the RIS-based information transmission systems, providing a comprehensive overview of state-of-the-art techniques in system and channel design. The discussion highlights the challenges posed by multipath fading, which complicates channel estimation due to the presence of both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) components. Then, introduce the image super-resolution model. Finally, the chapter distinguishes between two types of channel estimation: cascaded channel estimation, which simplifies the process by focusing on end-to-end links, and separate channel estimation, which requires accurate individual links between the source, RIS, and destination. RIS technology's ability to create configurable and controllable environments makes it a promising solution for future communication systems.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the simulation parameters, simulation results, and performance evaluation for all the proposed channel estimation schemes discussed in this thesis's methodology chapter. The performance of the proposed channel estimation solutions is evaluated using a MATLAB 2023a link-level simulator [24] and Anaconda. The performance metrics, such as system Capacity, Channel Gain, Normalized path loss, NMSE, BER, MSE, Throughput, and Time Complexity, are used to measure the performance of the proposed techniques and other existing methods. The results are presented in four sections based on the two deployed scenarios. The first section presents simulation parameters and results that consider the Least Square channel estimation evaluations for different multipath fading channel models for addressing the thesis's first objectives. The second section presents the simulation parameters and simulation results that consider the SRIR-ChNet downlink RIS-MIMO system for addressing the second objective. The third section presents simulation parameters and the simulation results that consider the PSBA-H cascaded and separate channel estimation uplink/downlink RIS-MIMO system for addressing the thesis's third objective. The last section is the Performance evaluation of all proposed channel estimation algorithms. These four sections are reflected in Section 4.3, Section 4.4, Section 4.5, and Section 4.6, respectively.

4.2 Validation and Analysis of the Dataset

This section of the thesis focuses on validating and analyzing the performance of the 5G dataset generation proposed in RIS-MIMO systems. We begin by examining the reliability of our input data through dataset validation, as detailed in subsection 4.2.1. This process ensures that the dataset used for training and testing the model is accurate and dependable. Next, we validate our results to confirm that the simulation environment produces outcomes that closely align with those obtained from related methods, as discussed in subsection 4.2.2. This thorough approach establishes a solid foundation for understanding the strengths and limitations of 5G RIS-MIMO technology.

In conclusion, the new dataset was generated to encompass all the necessary characteristics, including multipath fading, Reconfigurable Intelligent Surface (RIS), multi-base station (BS), and multi-user equipment (UE) scenarios, as well as the cascaded and separate channel matrices and phase shift matrix. This methodology ensures that the dataset accurately represents the complex and dynamic conditions inherent in RIS-MIMO systems, thereby providing a robust foundation for the channel estimation experiments.

4.2.1 Benchmark Validation Results

In this section of the thesis, we presented the validation results of the related works in terms of Mean Square Error and Capacity, currently compared with the CAE-ChannelNet [199], CBD-GAN [201], DQN, and DDL [126] algorithms. The

benchmark serves as a critical evaluation tool, allowing us to assess the effectiveness and efficiency of our model in comparison to established standards in the field. This validation result has been done to make sure that the simulation environment can give a very close result compared to CAE-ChannelNet, CBD-GAN, DQN, and DDL. The next sections will discuss the performance analysis for solving channel estimation problems for the proposed SRIR-ChNet and PSBA-H algorithms.

The first benchmark focused on a single communication link established between a pair of transmit (Tx) and receive (Rx) antennas. For this configuration, the channel time-frequency response channel matrix H , which has dimensions $N \times M$ and contains complex values, can be effectively represented as two separate 2D images one depicting the real part and the other representing the imaginary part, which is based on the Long-Term Evolution (LTE) standard with $N = 14$ time slots and $M = 72$ subcarriers. The benchmark treats the time-frequency response of a fast-fading channel matrix as a two-dimensional image. Building on this representation, it proposed CAE-ChannelNet, a comprehensive pipeline that utilizes advanced deep image processing techniques. This approach enables the accurate estimation of the channel response, enhancing the overall performance of the communication system. In this section of the thesis, the results of implementing the benchmark will be presented after designing the model and the data set from the benchmark [199]. After running the model and training the dataset, we obtained many errors, such as reshaping the dataset dimension after correcting all the errors. The model worked efficiently and gave the desired results.

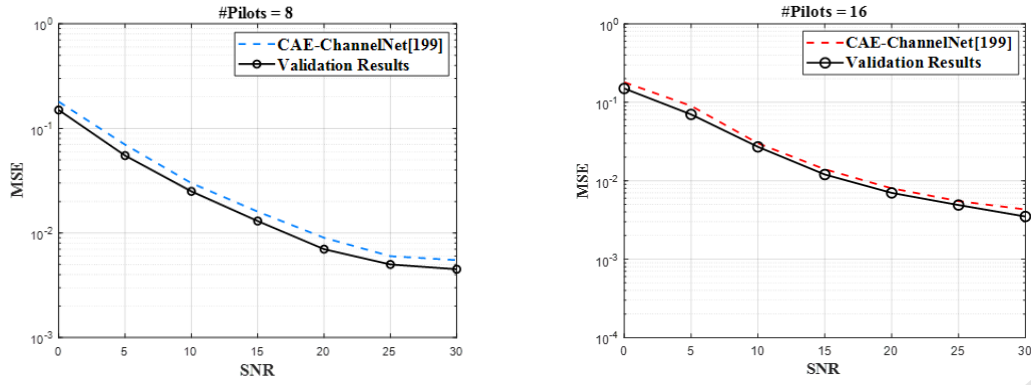


Figure 4.1: MSE results for 8 and 16 number of pilots

The validation of the benchmark in terms of Mean Square Error against Signal-to-Noise Ratio shows very close results compared to the proposed algorithm CAE-ChannelNet [199] due to the creation of these results was done under the same conditions used in the Vienna simulator [24], in other words, the same parameters were used with specifications of LTE as shown in Figures 4.1 and 4.2.

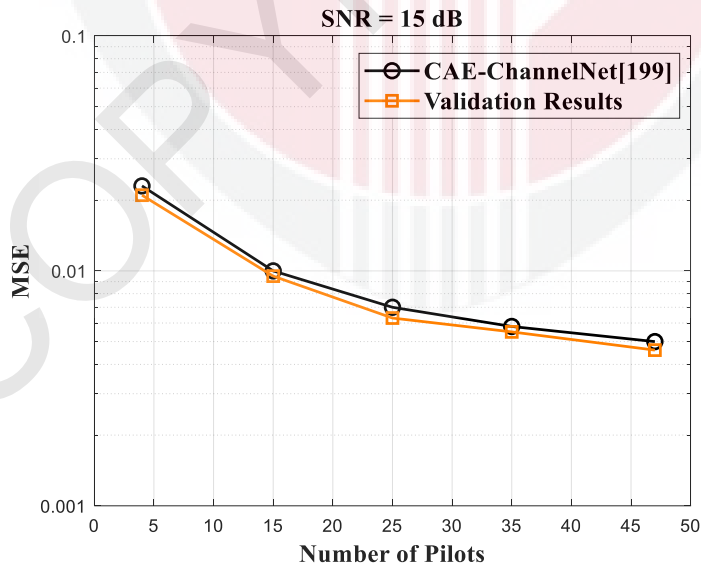


Figure 4.2: MSE results based on the number of pilots

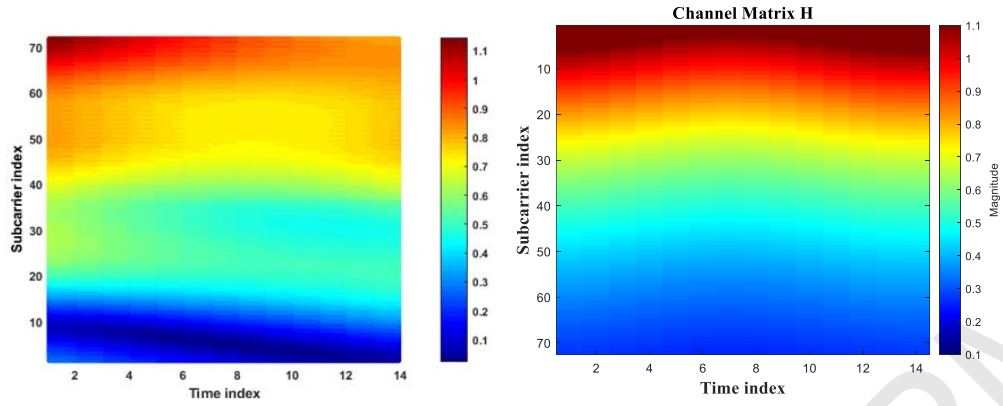


Figure 4.3: An example of a normalized real/imaginary 2D image channel matrix

Figure 4.3 shows the left image, which represents the benchmark results of the channel estimation model. In this image, the color gradient typically indicates the performance metrics, such as Mean Square Error (MSE) or Signal-to-Noise Ratio (SNR). Cooler colors (e.g., blue and green) suggest higher error rates or lower performance, while warmer colors (e.g., red and yellow) indicate better performance with lower error rates. A predominance of warmer colors signifies that the benchmark model performs well across most scenarios. In contrast, isolated cooler regions may highlight specific areas where the model struggles, possibly due to noise or interference. The right image depicts the validation results for the benchmark model. This image is crucial for assessing how well the model generalizes to new data. The color scheme in this image may show a similar gradient as in the benchmark. Still, it should ideally exhibit a more uniform distribution of warmer colors if the model has successfully learned from training data. A noticeable change in color from warmer to cooler tones suggests improved performance during validation, indicating that the model is robust and capable of accurately estimating channels in unseen scenarios. The change in color between the two images can be justified by considering factors such as the left image may reflect initial training results where the model has yet to fully converge, resulting

in higher errors. The subsequent training and validation processes refine the model's parameters, leading to improved accuracy. The right image's warmer colors indicate that the model has learned to generalize well from training data to validation scenarios, effectively adapting to variations in channel conditions. If validation results show significant improvements in color representation, it could also imply that noise-handling strategies were effectively implemented during training. Normalization of the channel matrix H in Figure 4.3 is essential for several reasons. Firstly, it standardizes the values within the matrix, ensuring consistency across different datasets and improving the efficiency of model training. Secondly, normalization enhances numerical stability during computations, which is crucial for deep learning models, particularly CNNs, by preventing large variations in input values that could slow down or destabilize training. It also ensures that all features contribute proportionally to the learning process, leading to faster convergence and improved generalization. While improper normalization could potentially distort certain channel characteristics, in this case, it preserves the essential structure of the channel response while making the learning process more efficient. Overall, normalization is a necessary preprocessing step that enhances the stability and performance of RIS-MIMO channel estimation algorithms without introducing significant loss of critical information.

The second benchmark focused on one RIS, one controller, one base station (BS) equipped with N antennas, and K user equipment (UEs) equipped with M antennas for the RIS- MIMO system, by leveraging the low-rank structure of RIS channels, practical residual neural networks, named convolutional blind denoising networks, convolutional denoising generative adversarial networks (GAN-CBD), and multiple residual dense networks, are proposed to obtain accurate channel state information,

which can reflect the impact of different methods on the estimation performance. Figure 4.4 presents the validation results are slightly better than the benchmark because the proposed GAN-CBD [201] model has likely been fine-tuned to handle specific noise conditions more effectively, leveraging the generative capabilities of GANs to reduce estimation errors. This can result in better generalization during validation, where the model benefits from the training data and optimization techniques, ultimately achieving lower NMSE compared to the benchmark under similar SNR conditions.

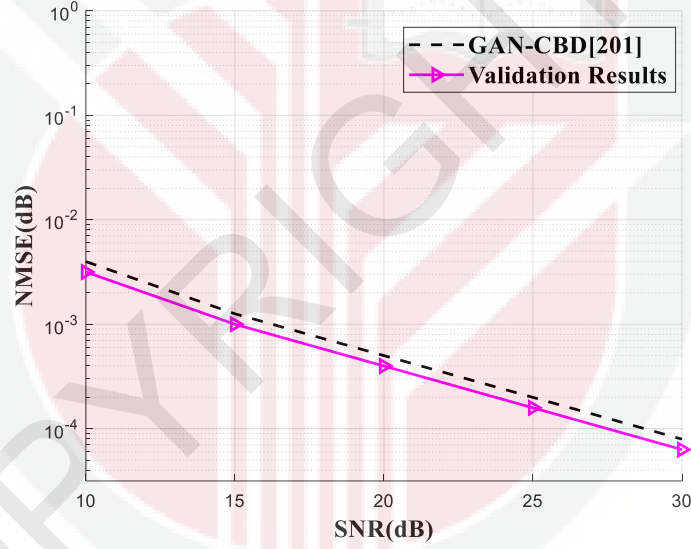


Figure 4.4: NMSE performance validation results for the proposed GAN-CBD [201]

For objective three, The benchmark setup consisted of an N antenna source node (S), an M antenna destination node (D), and an RIS composed of K fully passive reflecting elements. It operated under the assumption that severe blocking or deep fading prevented a direct link between S and D.

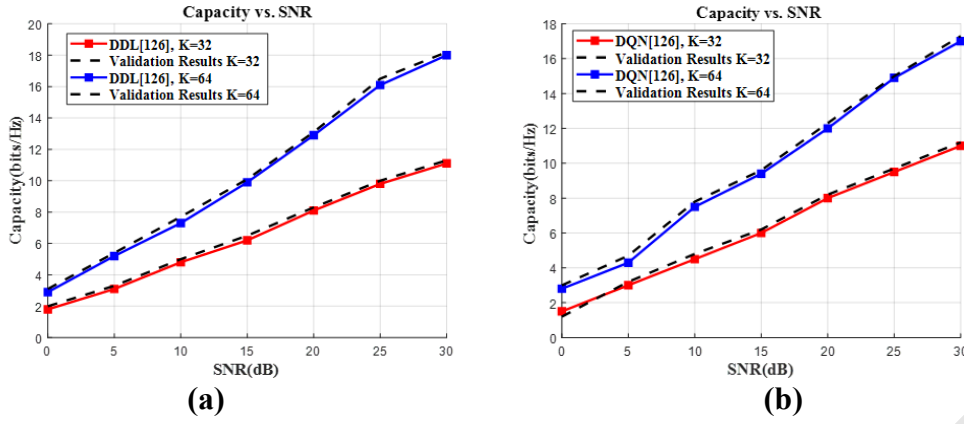


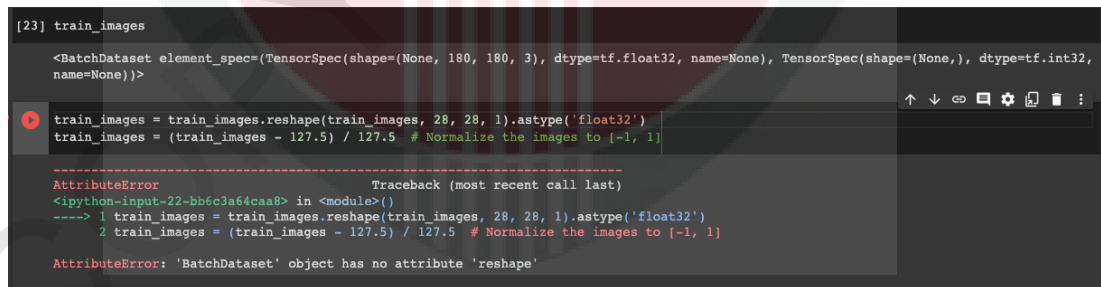
Figure 4.5: Validation results for the proposed DDL[126] and DQN [126] where the number of RIS elements $K=32$ and $K=64$ (a) MIMO network (b) MISO network

Figure 4.5 shows two different algorithms (DDL and DQN) for optimizing phase shifts and beamforming in a RIS-MISO and RIS-MIMO network, with two antenna elements at both the source and destination nodes. The performance metric shown is the network capacity (in bits/Hz) as a function of SNR (signal-to-noise ratio) for two different numbers of RIS elements, $K=32$, and $K=64$. The validation results for DDL and DQN are very close to the original curve, especially as the number of RIS elements increases from $K=32$ to $K=64$. This suggests that both algorithms achieve similar performance in terms of capacity, particularly in higher SNR regions. The closeness of the results can be explained by the fact that both DDL and DQN algorithms are designed for accurate channel estimation and optimization of phase shifts and beamforming vectors. Since both algorithms work towards the same objective (maximizing the capacity by optimizing the RIS elements), their performance will converge. The algorithms have different optimization methods, but since they both target the same objective function (maximizing capacity), the solutions they find may not differ significantly. The closeness of validation results compared to DDL and DQN can be justified by the fact that all methods aim to optimize the same variables (phase shifts and beamforming

vectors) to maximize the system capacity. Given accurate channel estimation, similar optimization goals, and the nature of RIS-MIMO systems, it is expected that all methods will converge to near-optimal solutions, especially when the number of RIS elements and SNR are increased. Additionally, both DDL and DQN, being deep learning-based, are likely to generalize well, producing similar results when trained and validated under similar conditions.

4.2.2 Validation and Analysis of 5G Dataset Generation in RIS-MIMO

This section of the thesis presented a rigorous validation of the proposed 5G RIS-MIMO dataset, and then this research compares the proposed dataset with existing datasets used in similar studies, ensuring its accuracy and representativeness. This thorough validation process strengthens the credibility of this thesis's findings and provides a solid foundation for future research in the field of 5G RIS-MIMO systems.



```
[23] train_images
<BatchDataset element_spec=(TensorSpec(shape=(None, 180, 180, 3), dtype=tf.float32, name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>

train_images = train_images.reshape(train_images, 28, 28, 1).astype('float32')
train_images = (train_images - 127.5) / 127.5 # Normalize the images to [-1, 1]

AttributeError                                Traceback (most recent call last)
<ipython-input-22-bb6c3a64caa8> in <module>()
----> 1 train_images = train_images.reshape(train_images, 28, 28, 1).astype('float32')
      2 train_images = (train_images - 127.5) / 127.5 # Normalize the images to [-1, 1]

AttributeError: 'BatchDataset' object has no attribute 'reshape'
```

Figure 4.6: Dataset image validation Error due to different dimensions

First part of this section, we utilized the benchmark dataset to train our proposed model. Upon execution, an error was encountered, as illustrated in Figure 4.6. The source of this error stems from a dimensional mismatch between the data and the requirements of our proposed model. Following a programmatic adjustment to align

the data with the specifications of our model, we obtained the results for the mean square error and accuracy, as depicted in Figures 4.7 and 4.8.

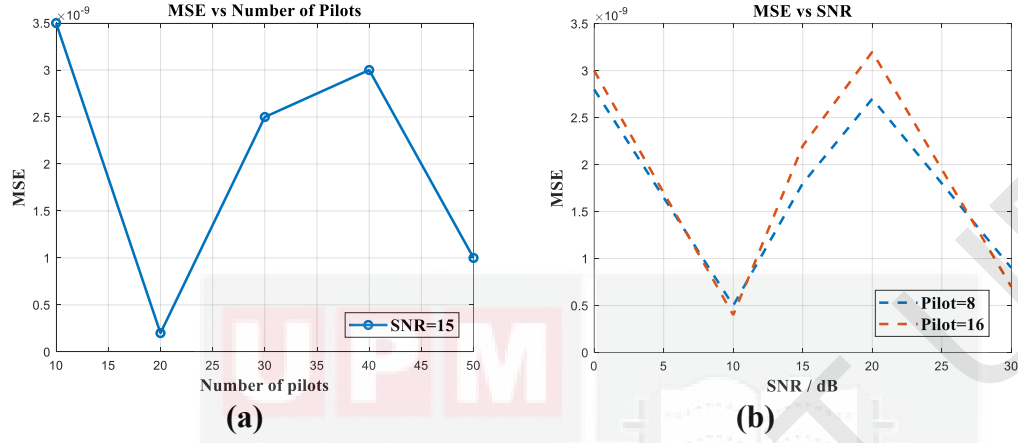


Figure 4.7: (a) MSE vs. Number of pilots (b) MSE vs. SNR validation of SRIR-ChNet using a dataset of the CAE-ChannelNet model [199]

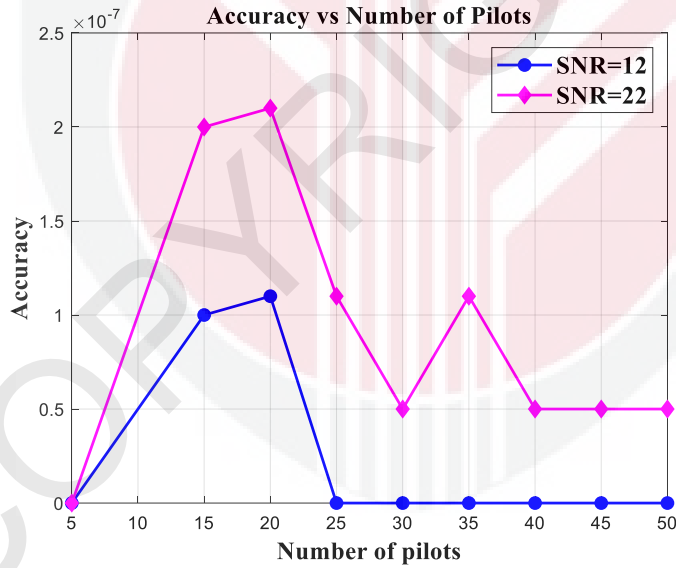


Figure 4.8: Accuracy validation of SRIR-ChNet using a dataset of the CAE-ChannelNet model [199]

The significant discrepancies observed in the results can be attributed to the incompatibility of the data with our proposed model, which arises from several factors. First, the benchmark data was generated in a physical environment that possesses

characteristics distinct from those required by our proposed model. Specifically, while the benchmark utilized a single antenna for both transmission and reception, our model employs a Multiple Input Multiple Output (MIMO) configuration with $N \times M$ antennas at each base station (BS) and user equipment (UE). Second, our proposed model incorporates multiple users and base stations, along with the integration of Reconfigurable Intelligent Surfaces (RIS) between them. In contrast, the benchmark only involved one user equipment (UE) and one base station (BS), without any smart reflective surfaces. Third, it is important to note that the benchmark data was generated based on 4G (LTE) characteristics, whereas our proposed model is designed to operate under 5G specifications. Due to the aforementioned reasons, we were unable to utilize the dataset specific to the benchmark. Consequently, we generated a new dataset that incorporates modern features and advantages, designed for more advanced environments. This approach aims to yield improved results compared to the benchmark. The second part of this section presents the results illustrated in Figures 4.9 and 4.10, which demonstrate that the benchmark model was trained using our newly generated dataset. As depicted in Figure 4.9, the results indicate a significant improvement in the mean square error when compared to the benchmark dataset. This enhancement can be attributed to the fact that our data was generated in an environment characterized by modern and advanced features, as well as reduced noise levels due to the incorporation of Reconfigurable Intelligent Surfaces (RIS). This integration minimizes signal scattering caused by obstacles and effectively focuses signal energy toward the receiver. Figure 4.10 provides a representation of our channel in the form of a two-dimensional time-frequency response for two types of channels: ideal and noisy. Both channel representations show a color gradient that goes from blue to green, yellow, orange, and dark red, and no color interference. This indicates

that our dataset was generated with strong power signals and minimal noise, resulting in superior performance compared to the standard dataset implementation within the model.

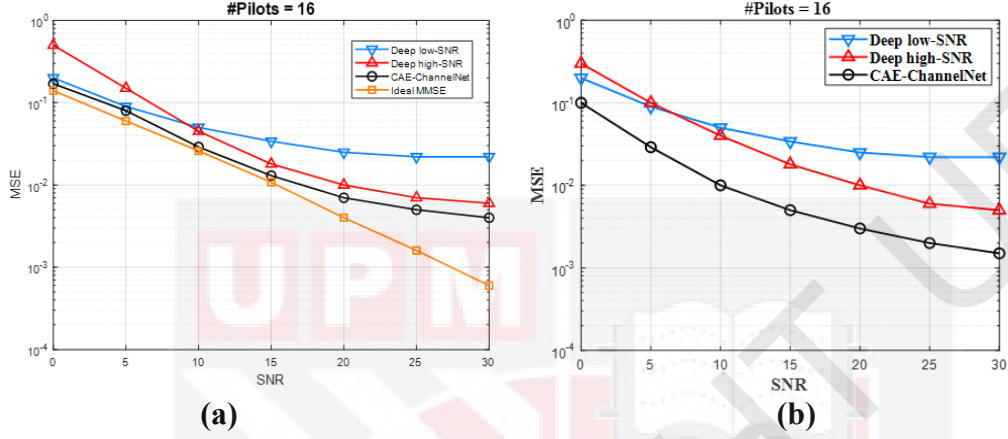


Figure 4.9: (a) MSE Vs. SNR using CAE-ChannelNet [199] original figure, (b) MSE Vs. SNR using CAE-ChannelNet [199] with the proposed dataset

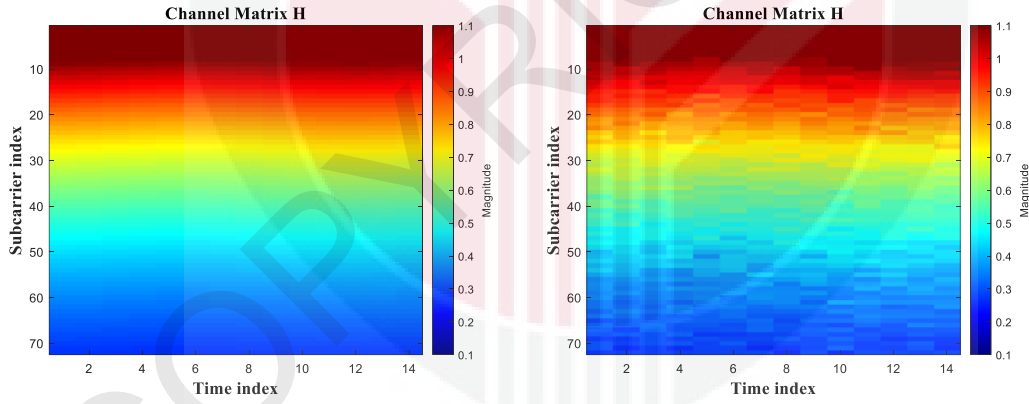


Figure 4.10: Two 2D image perfect and noisy channel matrices for our proposed SRIR-ChNet

Figure 4.11 presents the results of implementing and training the proposed dataset using another benchmark model, GAN-CBD [201], which possesses physical characteristics closely aligned with our proposed scenario. This model incorporates multiple base stations (BS) and user equipment (UE), each equipped with multiple

antennas and a Reconfigurable Intelligent Surface (RIS) to direct signal energy toward the receiver.

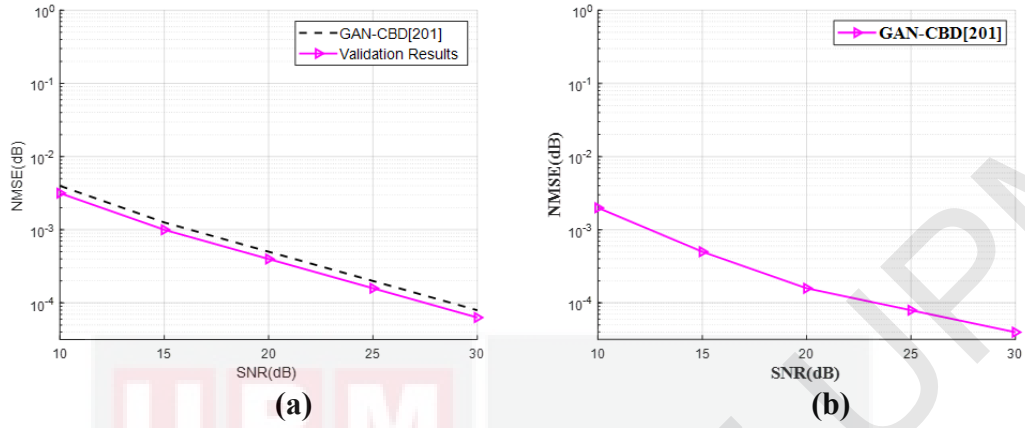


Figure 4.11: (a) NMSE against SNR using GAN-CBD [201] original figure, (b) NMSE against SNR using GAN-CBD [201] with the proposed dataset

While this configuration is similar to our proposed scenario, it does not address the issue of signal scattering caused by multipath fading. To further validate the proposed dataset, we also trained it using a model based on convolutional neural networks (CNNs) that process images. The results indicate that our proposed dataset outperformed the benchmark dataset, confirming its efficacy for the intended application.

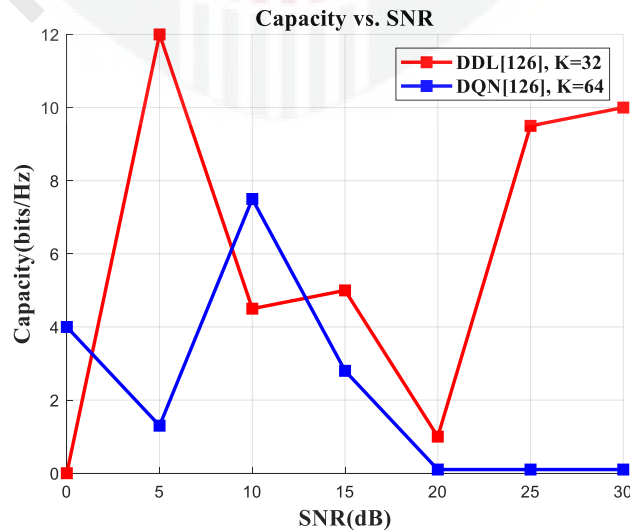


Figure 4.12: Capacity performance for DDL and DQN dataset using PSBA-H

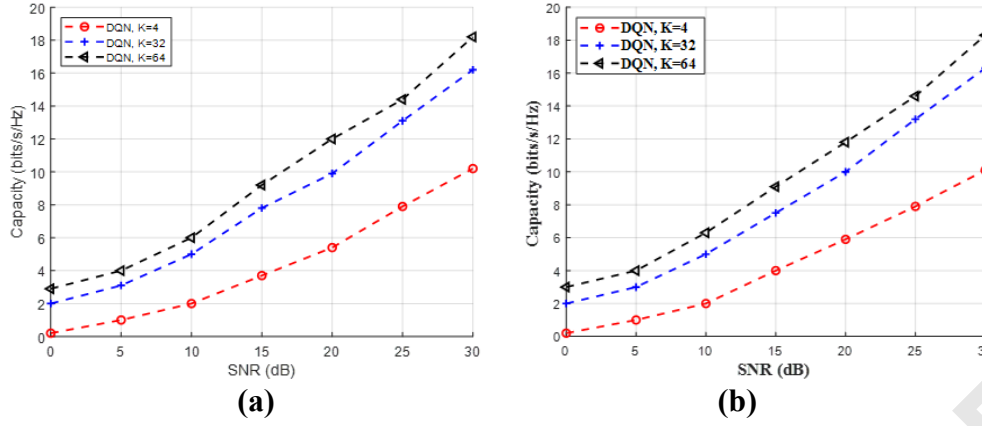


Figure 4.13: (a) Capacity performance against SNR in RIS-MIMO using DQN [126] original figure, (b) Capacity performance against SNR using DQN [126] with the proposed dataset

In this section, we validate the dataset proposed for the third objective of this thesis. The communication system from which the dataset was generated is characterized by a single base station (BS) and a single user equipment (UE), both equipped with multiple antennas and fully passive elements in the Reconfigurable Intelligent Surface (RIS) positioned between them. This system operates under 5G characteristics, which closely align with those of the proposed communication system.

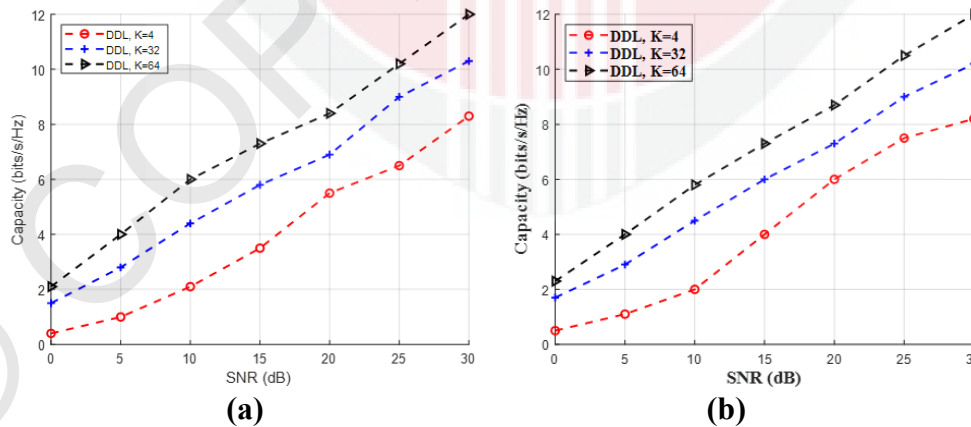


Figure 4.14: (a) Capacity performance against SNR in RIS-MISO using DDL [126] original figure, (b) Capacity performance against SNR using DDL [126] with the proposed dataset

When the benchmark data was utilized to train our proposed model, PSBA-H we encountered incorrect results as shown in Figure 4.12 despite the similarities between the two communication systems from which the dataset was derived. This discrepancy can be attributed to several factors: Random Generation of Matrices: The cascaded channel matrix and phase shift matrix were generated randomly, which is not compatible with our proposed model that relies on a dataset based on time and frequency response. Furthermore, there were no matrices representing separate channels. Passive Reflective Surfaces: The reflective surfaces employed to reflect signals were entirely passive and lacked active elements necessary for signal estimation within the RIS. Due to these limitations, the benchmark dataset was deemed unsuitable, prompting the proposal of a scenario with enhanced characteristics. Figures 4.13 and 4.14 illustrate the capacity results for the benchmark DDL and DQN models using the proposed dataset for both algorithms based on deep learning. The results indicate a slight superiority in terms of capacity obtained from the benchmark dataset.

4.3 Performance Evaluations for Channel Estimation using Least Square for Different Channel Models in MIMO-OFDM Systems

This section evaluates the performance of the proposed RIS-MIMO downlink systems without channel estimation, exploring different fast-fading channel models, including Additive White Gaussian Noise (AWGN), Rician, and Rayleigh channels, while implementing 64-QAM modulation. The performance of the Least Square (LS) channel estimation method is then assessed by comparing the Bit Error Rate (BER), Throughput, and Mean Squared Error (MSE) for the 64-QAM modulation, in AWGN, Rayleigh, and Rician channels. Their performance is compared with the method proposed in [198].

4.3.1 Simulation Setup and Parameter Specifications

In this thesis, the MATLAB simulator simulate the performance comparison between the proposed scenarios. The simulated output is a comparison of BER, MSE, and Throughput for different channel models in the context of Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions without channel estimation and with an LS estimator with a new pilot design for different modulation techniques. The communication systems involve two BSs, a UE, and one RIS controlled by an RIS controller at the BS. The simulated environment is based on the 5G system's air interface standard, utilizing time-frequency resource slots with a total of 72 subcarriers and 14 OFDM symbols. The experiment uses a 2.5 GHz frequency, a 1.6 MHz bandwidth, and a 1730 ns delay spread, all of which are specific to the PedA channel model. The performance of the proposed scenario is evaluated using the PedA channel model across a signal-to-noise ratio (SNR) range corresponding to noise levels between 0 and 35 dB. In the Rician scenario, the RIS communication in both LOS and NLOS scenarios reflects the signal to the UE with a reflection power of -75 dB, while the BS can still have a direct connection with the UE. In the Rayleigh scenario, the direct path is blocked, creating an NLOS scenario. Here, the RIS plays a critical role by reflecting the blocked signal to the UE, ensuring communication despite the obstruction, with the same -75 dB reflection power. The summary of the simulation parameter values considered for the RIS-MIMO system is the 5G propagation environment standards and is given in Table 4.1 as obtained from [198].

Table 4.1: The Simulation Parameters Setup

Parameter	Value
MIMO	2 x 2
No. of BS, UE, RIS	2, 2, 1
Simulation	Downlink
FFT size	64
Subcarrier spacing	15 kHz
Cyclic prefix	16
Type of modulation	OFDM 64 QAM
Maximum Doppler frequency	138 Hz
Noise model	Gaussian Noise
Sample frequency	3.84 MHz
No. of Sub-carriers	72
Time Slot	14
Fading	Rayleigh, Rician
Frame Structure	FDD
Channel Power Delay Profile	PedestrianA
Channel Estimation Method	Approximate-Perfect, Pilot Aided LS
Pilot Pattern Uplink/Downlink	Diamond
Rician Factor	10

4.3.2 Simulation Results

This section presents the simulation results and evaluation performance of the proposed Least Square-based OFDM-RIS-MIMO in comparison with the existing techniques. The performance evaluation is carried out in terms of some measurement metrics such as Bit Error Rate, Throughput, and MSE. The simulation is performed using a MATLAB simulator.

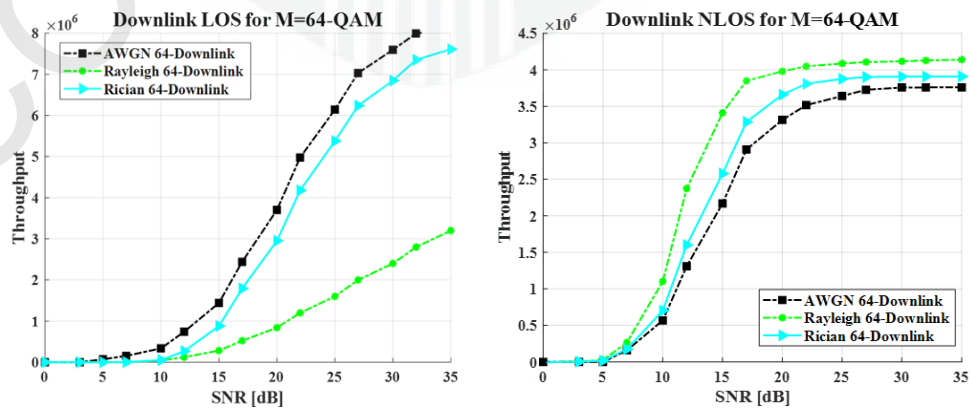


Figure 4.15: The performance of the throughput in AWGN, Rayleigh, and Rician channels without channel estimation for M=64-QAM

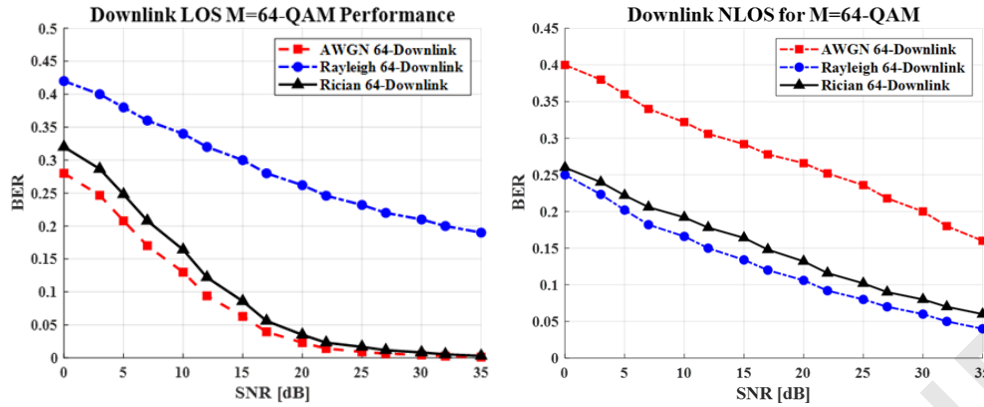


Figure 4.16: The Bit Error Rate performance in AWGN, Rayleigh, and Rician channels without channel estimation for M=64-QAM

Figure 4.15 illustrates the performance of the Bit Error Rate (BER) across different channel conditions, specifically AWGN, Rayleigh, and Rician channels, without channel estimation for M=64-QAM. In Line-of-Sight (LOS) conditions, the Rician fading model demonstrates significantly lower BER compared to Rayleigh fading. The performance in AWGN is optimal as expected since there is no multipath interference. This is primarily due to the presence of a strong LOS component, which enhances signal clarity and reduces interference from multipath effects. Conversely, under Non-Line-of-Sight (NLOS) conditions, the AWGN fading model exhibits a higher BER due to increased multipath interference and the absence of a direct path. The Rician model still performs better than AWGN in NLOS scenarios, but shows a marked increase in BER as the NLOS paths dominate. Rayleigh shows better performance in the NLOS scenario. These results highlight the critical role that multipath fading plays in determining communication reliability in RIS-MIMO systems.

Figure 4.16 presents the throughput performance across AWGN, Rayleigh, and Rician channels for M=64-QAM. In LOS conditions, the throughput is markedly higher in AWGN no fading compared to Rician fading and Rayleigh showed the worst

performance due to the favorable signal propagation characteristics provided by the LOS path. The clear direct link allows for more efficient data transmission, resulting in enhanced throughput values. However, in NLOS scenarios, there is a noticeable decline in throughput for both AWGN and Rician models compared with Rayleigh showing the best performance. The lack of a direct path leads to increased delays and lower effective data rates, with both models converging towards similar throughput levels as multipath effects become more pronounced. This emphasizes how multipath fading can severely impact throughput performance in RIS-MIMO systems.

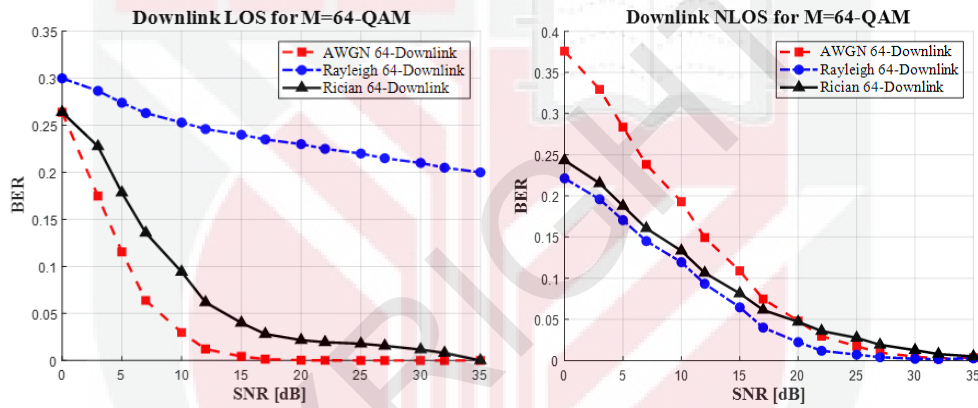


Figure 4.17: Comparison of LS Estimators' BER in an M=64-QAM across AWGN, Rayleigh, and Rician Channels

Figure 4.17 compares the Bit Error Rate (BER) performance of Least Square (LS) estimators across AWGN, Rayleigh, and Rician channels for M=64-QAM. In LOS scenarios, LS estimators perform optimally in Rician fading due to the presence of a strong LOS component that aids in accurate channel estimation. However, in NLOS conditions, LS estimators show better performance under Rayleigh fading compared to Rician fading. This is likely because Rayleigh fading captures the multipath effects more effectively when no direct path exists, leading to improved estimation accuracy despite the inherent challenges of NLOS environments.

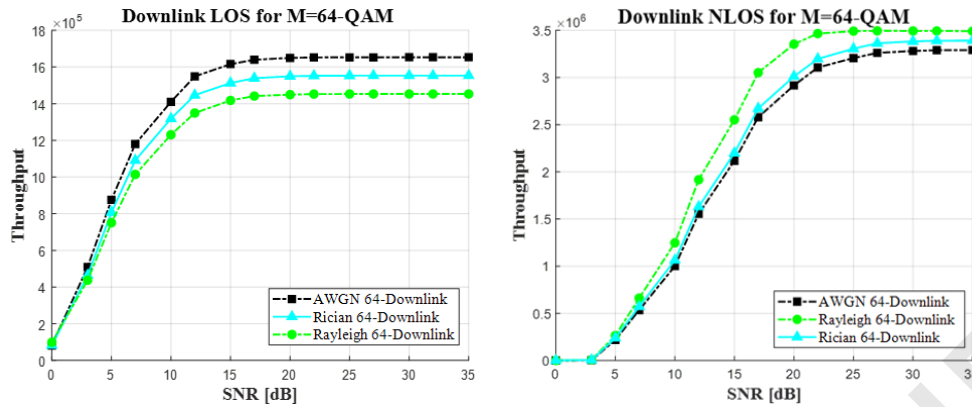


Figure 4.18: Comparison of LS Estimators' Throughput in a 64-QAM for AWGN, Rayleigh, and Rician Channel

Figure 4.18 illustrates the throughput performance of LS estimators across different channel conditions. In LOS scenarios, Rician fading yields higher throughput due to its favorable propagation characteristics from the direct path, allowing for more efficient data transmission. Conversely, under NLOS conditions, both AWGN and Rician models exhibit reduced throughput; however, Rayleigh fading maintains better performance due to its ability to handle multipath interference more effectively when no direct path is present.

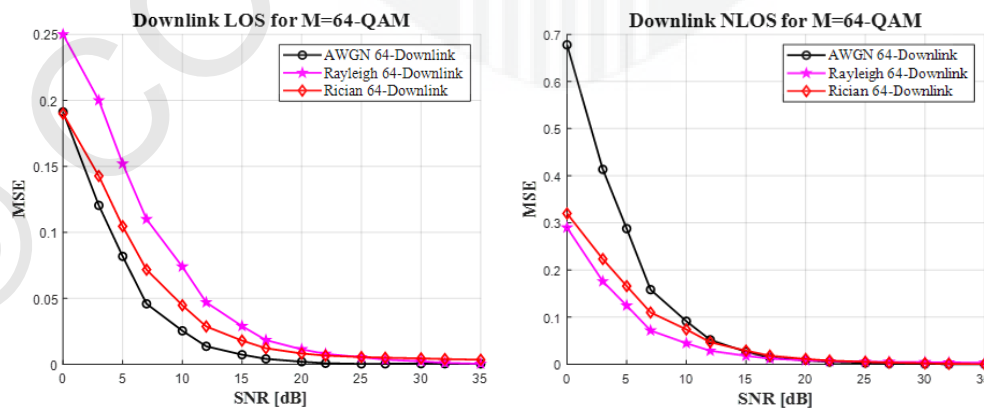


Figure 4.19: LS estimators' Mean Squared Error (MSE) performance in AWGN, Rayleigh, and Rician channels for M=64-QAM

Figure 4.19 shows the Mean Squared Error (MSE) performance of LS estimators across AWGN, Rayleigh, and Rician channels for M=64-QAM. In LOS conditions, MSE is minimized in Rician fading due to the strong LOS component that facilitates accurate channel estimation. Under NLOS conditions, however, Rayleigh fading results in lower MSE compared to Rician fading because it effectively models the multipath environment without a direct path, leading to better estimation accuracy despite increased interference.

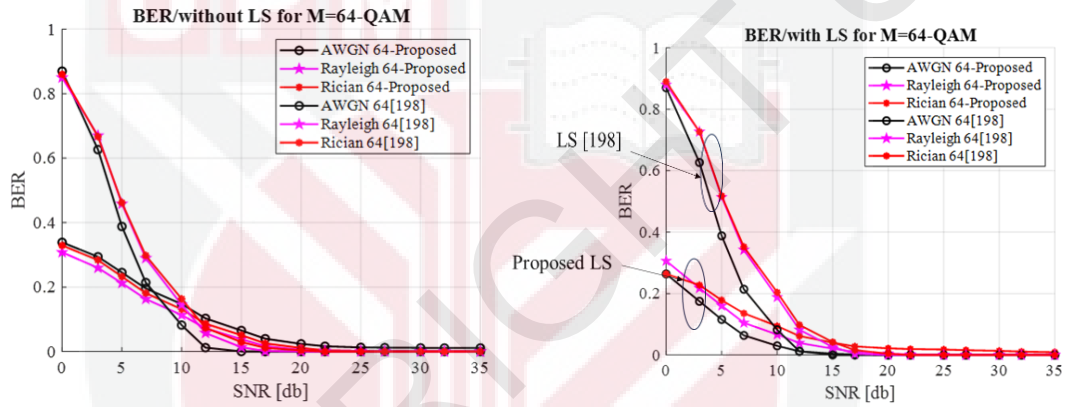


Figure 4.20: Illustrates the BER performance without channel estimation, and the BER performance of LS estimators in AWGN, Rayleigh, and Rician channels for 64-QAM

Figure 4.20 illustrates the Bit Error Rate (BER) performance between channels without an estimator and pilot-aided Least Square (LS) channel estimation across various multipath fading scenarios. The results demonstrate the effectiveness of applying the LS estimator, particularly with the newly designed diamond-shaped pilot signals. In scenarios without LS estimation, the BER ranges from 0.36 to 0.38 dB, indicating a relatively high error rate due to the lack of accurate channel information. In contrast, when employing the LS estimator with the optimized pilot design, the BER improves significantly, showing a minimum error range of 0.25 to 0.29 dB. The performance of

different types of fading, specifically Rayleigh and Rician, varies significantly between Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios, impacting communication reliability in RIS-MIMO systems.

In LOS conditions, the Rician fading model generally outperforms Rayleigh fading. The presence of a strong LOS component in Rician fading enhances signal clarity and reduces the effects of multipath interference, leading to lower Bit Error Rates (BER) and higher throughput. This advantage is evident in the results, where Rician fading consistently demonstrates better performance metrics compared to Rayleigh fading, making it the preferred model for environments where a direct path exists.

Conversely, in NLOS conditions, Rayleigh fading tends to show better performance than Rician fading. In these scenarios, the absence of a direct path means that multipath effects dominate, and Rayleigh fading effectively captures these characteristics. As a result, Rayleigh fading can provide more reliable channel estimation and lower BER under NLOS conditions. The Rician model struggles in these situations due to its reliance on a weak or absent LOS component, which leads to higher error rates.

Overall, the findings indicate that Rician fading is optimal in LOS scenarios due to its favorable propagation characteristics, while Rayleigh fading performs better in NLOS conditions by accurately modeling multipath effects when no direct path is available. The AWGN channel results in the worst performance because the direct path between the BS and UE is completely blocked, causing severe signal attenuation. Without a clear line of sight, the received signal strength is significantly reduced, leading to increased noise dominance and performance degradation. Understanding the different

fading mechanisms, specifically Rayleigh and Rician fading, allows for a more nuanced approach to channel estimation and optimization in RIS-MIMO systems. Firstly, multipath fading significantly impacts communication reliability. By examining both direct (LOS) and reflected (NLOS) environments, the review highlights how these fading types affect signal propagation, leading to variations in Bit Error Rate (BER) and throughput. This understanding is essential for designing effective communication systems that can adapt to varying environmental conditions. Secondly, the review provides insights into how smart reflective surfaces can mitigate the adverse effects of multipath fading. By strategically manipulating phase shifts at the RIS, it is possible to enhance signal quality and improve overall system performance. This aspect is particularly important as it opens avenues for optimizing channel estimation techniques tailored to specific fading scenarios. In summary, the first objective of this thesis is vital as it not only deepens our understanding of multipath fading in RIS-MIMO systems but also lays the groundwork for developing innovative solutions to enhance communication reliability and efficiency.

After we investigated each type of fading and applied it to the CNN model based on the channel environment. Rician fading was used for the cascaded and separate channels because it works well in environments with both line-of-sight (LOS) and non-line-of-sight (NLOS) paths, which reflects the nature of the channel when the direct path is partially blocked. On the other hand, Rayleigh fading was applied in the SRIR cascaded channel estimation, as it is more suitable for NLOS scenarios where the direct path is fully blocked and only multipath components are present.

4.4 Performance Evaluations for Channel Estimation using SRIR-ChNet in RIS-MIMO System.

This section assesses and validates the performance of the proposed SRIR-ChNet downlink cascaded channel estimation model in the RIS-MIMO system. The performance is compared with the channel estimation method that used the least square (LS), interpolated minimum mean square error (interpolated MMSE), CAE-ChannelNet [199], and GAN-CBD [201].

4.4.1 Simulation Setup and Parameter Specifications

In this scenario, we employ link-level simulation to evaluate the efficacy of the SRIR-ChNet network's cascaded channel estimation in a RIS-MIMO environment. Our simulation environment features a system with a 2-antenna base station (BS), a 2-antenna user equipment (UE), and a K -element intelligent reflecting surface (RIS). The RIS elements are assumed capable of continuous phase adjustment, with specific settings referenced from Tang et al. [235]. The cascaded channel follows a Rayleigh fading model, and users are randomly distributed near the RIS within a 3.5m to 15m range. The OFDM signal structure consists of 72 subcarriers and 14 time symbols per frame, with a maximum cascaded channel delay spread (L) of 5 ns. To train and evaluate the SRIR-ChNet, noisy channel datasets were generated using the PedA channel model, covering an SNR range from 0 to 35 dB. Detailed simulation parameters are summarized in Table 4.2. For performance comparison, we benchmark the SRIR-ChNet against several estimation methods, including the Least Square (LS), interpolated minimum mean square error (interpolated MMSE), CAE-ChannelNet [199], and GAN-CBD [201]. For training SRIR-ChNet, we used the Adam optimizer

(learning rate: 0.001, batch size: 400). The dataset comprised 40,000 channel realizations (from different users at the UE), divided into 30,000 for training, 5,000 for validation, and 5,000 for testing. This research adopts the mean square error (MSE) as its primary assessment metric to juxtapose the forecasted channel value with its counterpart. The summary of the simulation parameter values considered for the RIS-MIMO system is the 5G propagation environment standards, and are given in Table 4.2, and most of them are obtained from [199][201].

Table 4.2: The parameter setup for the RIS-MIMO system

Parameters	Values
Antenna Gain, RIS, BS, UE	8,21,21 dB
Distance of RIS-BS	100m
Simulation	Downlink
The Nearest Distance between users and BS	102m
The Nearest Distance of User-RIS	3.5m
Width of Reflecting Elements	0.012m
Length of Reflecting Elements	0.012m
Noise model	Gaussian Noise
No. of Sub-carriers	72
Time Slot	14
Fading	Rayleigh
Frame Structure	FDD
Channel Power Delay Profile	PedA
Channel Estimation Method	Approximate-Perfect, Pilot-Aided LS
Pilot Pattern Downlink	Diamond

4.4.2 Simulation Results

This section presents the simulation results and evaluation performance of the proposed SRIR-ChNet-based downlink cascaded channel estimation in RIS-MIMO in comparison with the existing techniques. The performance evaluation is carried out in terms of some measurement metrics such as MSE vs. Number of Pilots, MSE vs. Number of RIS Elements, MSE vs. Number of Antennas, and Time Complexity. The simulation is performed using a MATLAB simulator.

4.4.2.1 MSE vs. Number of Pilots

In this section, we analyze the relationship between channel estimation's Mean Squared Error (MSE) and the number of pilots used in RIS-MIMO systems. The figures illustrate how varying the number of pilots impacts MSE under different Signal-to-Noise Ratio (SNR) conditions.

Figure 4.21 presents the Mean Squared Error (MSE) of channel estimation for both training and validation phases at an SNR of 10 dB and 20 dB, using 8 pilots. The results indicate that as the SNR increases, the MSE decreases significantly, demonstrating improved channel estimation accuracy. The use of 8 pilots provides a baseline for evaluating performance; however, the relatively higher MSE values suggest that this number of pilots may not be sufficient for optimal performance in environments with high multipath fading.

In Figure 4.22, the MSE is evaluated with an increased number of pilots (16) at the same SNR levels. The results show a marked reduction in MSE compared to Figure 4.21, indicating that increasing the number of pilots enhances the channel estimation accuracy. This improvement can be attributed to the additional information provided by the increased pilots, which helps mitigate the effects of noise and multipath interference, leading to more reliable channel state information.

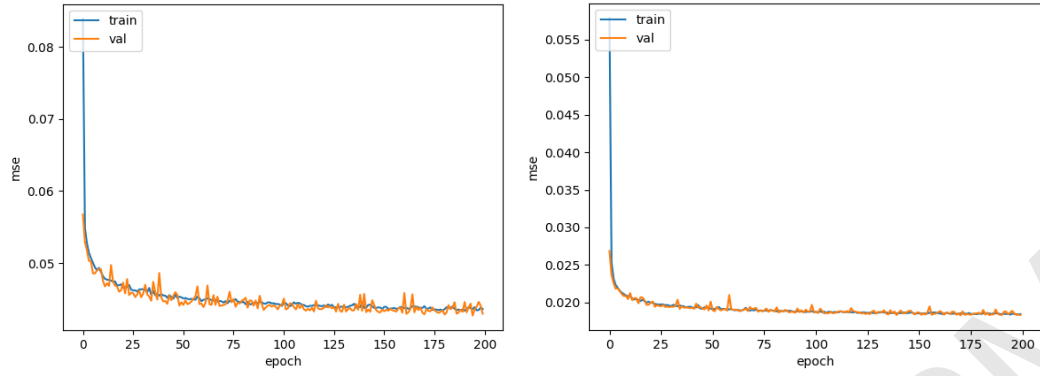


Figure 4.21: MSE channel estimation for training and validation (a)SNR=10 & pilot=8 (b) SNR=20 & pilot =8

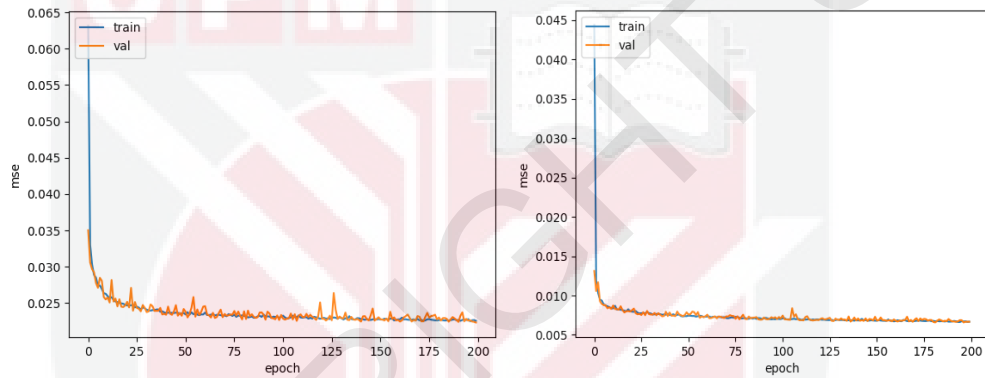


Figure 4.22: MSE channel estimation for training and validation (a)SNR=10 & pilot=16 (b) SNR=20 & pilot=16

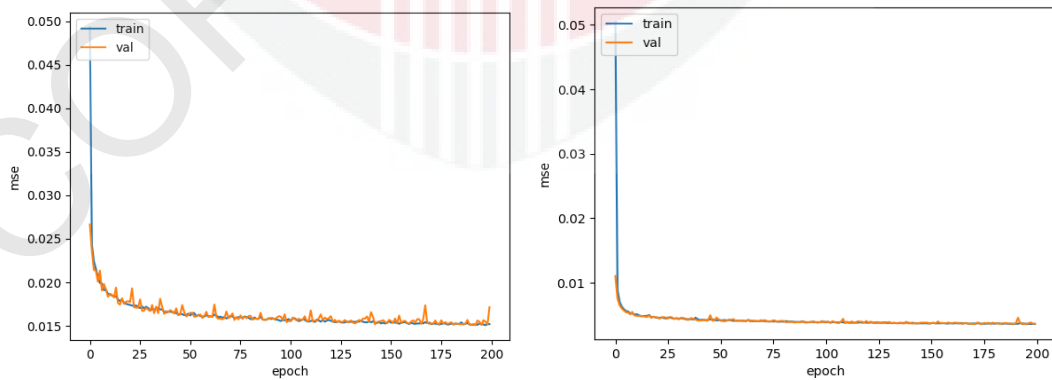


Figure 4.23: MSE channel estimation for training and validation (a)SNR=10 & pilot=24 (b) SNR=20 & pilot=24

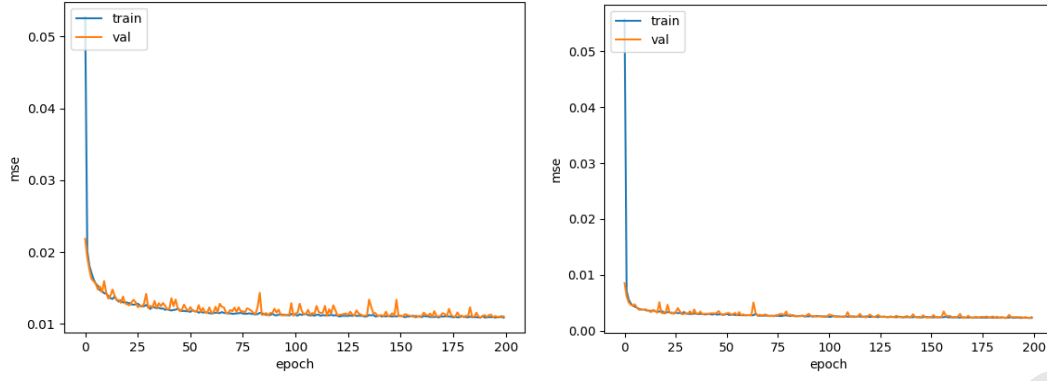


Figure 4.24: MSE channel estimation for training and validation (a)SNR=10 & pilot=36 (b) SNR=20 & pilot=36

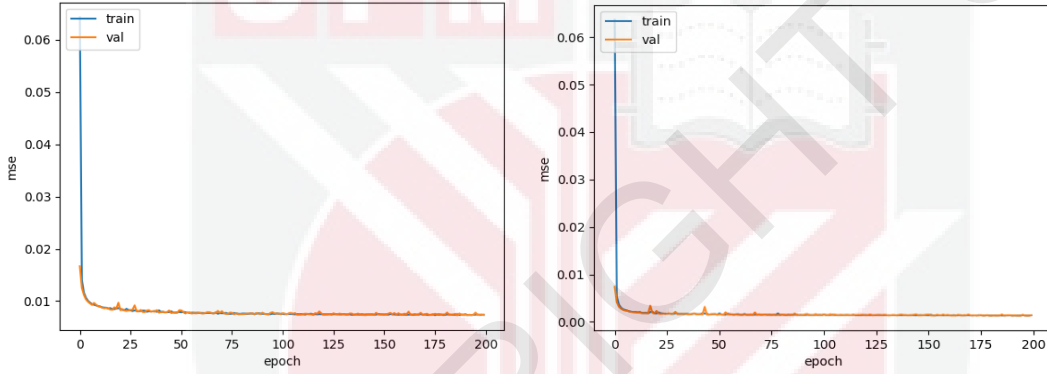


Figure 4.25: MSE channel estimation for training and validation (a)SNR=10 & pilot=48 (b) SNR=20 & pilot=48

Figures 4.23, 4.24 and 4.25 present results with an even greater pilot count (24, 36, and 48). The MSE values show a continued decline at both SNR levels, reinforcing the conclusion that increasing pilot numbers significantly enhances estimation accuracy.

This suggests that while increasing pilots enhances performance, there is a balance to be struck between pilot overhead and estimation accuracy. The SRIR-ChNet achieves the best performance in terms of MSE. Furthermore, the pilot count directly influences the input data dimensions for DL-based estimators, which in turn affects their channel estimation accuracy. Predictably, increasing the number of pilots improves the performance of all considered algorithms. The reason differs: analytical estimators like

LS, LMMSE, CAE-ChannelNet [199], and GAN-CBD [201] benefit from enhanced interpolation accuracy with more pilots. In contrast, DL-based estimators such as CAE-ChannelNet and SRIR-ChNet leverage the larger input data (from more pilots) to extract richer spatial features via their CNNs, leading to better results.

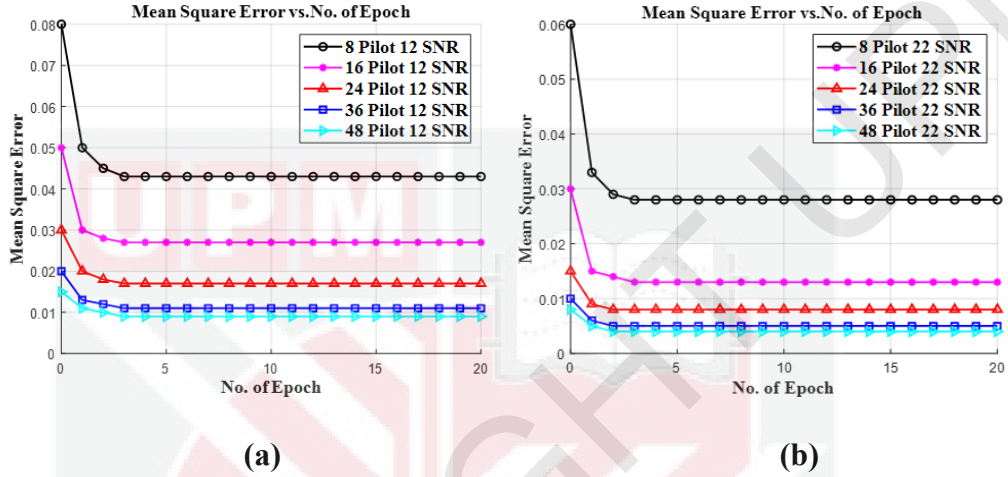


Figure 4.26: Mean square error for channel estimation in terms of pilot number(a) at SNR 12, (b) at SNR 22

Overall, these Findings highlight the critical role of pilot design in optimizing channel estimation accuracy in RIS-MIMO systems, as shown in Figure 4.26. Increasing the number of pilots and arranging the pilots along both time and frequency axes with given periods in a diamond-shaped constellation significantly reduces MSE across various SNR conditions. Ultimately, optimizing pilot numbers is essential for achieving effective channel estimation while managing resource constraints in practical applications.

4.4.2.2 MSE vs. Number of RIS Elements

In this section, we explore the relationship between the Mean Squared Error (MSE) of channel estimation and the number of Reconfigurable Intelligent Surface (RIS) elements in RIS-MIMO systems.

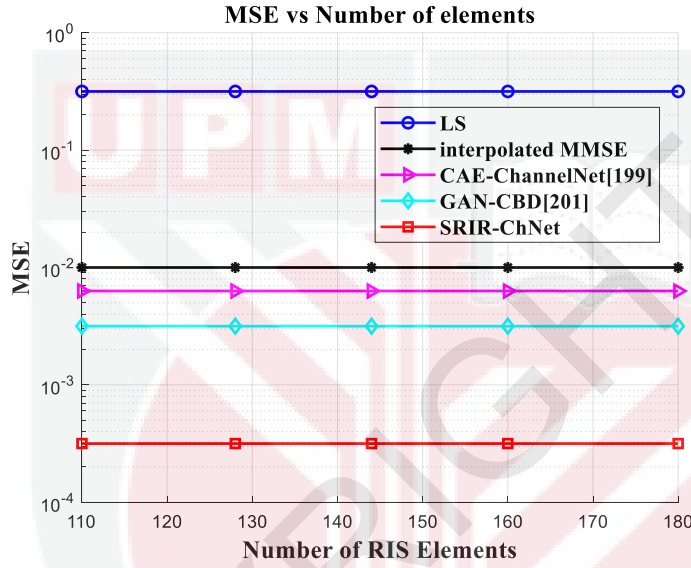


Figure 4.27: Performance of MSE for the channel under SNR = 10dB, and 8 pilots

The MSE performance demonstrates low sensitivity to the number of RIS elements, K . This occurs because, within our system model, the dimensionality of the channel matrix under estimation remains constant regardless of K , thus keeping the input data size fixed. Consequently, the MSE of the evaluated methods exhibits only slight variations as K increases. Despite this general trend, our proposed SRIR-ChNet consistently achieves the best performance, attributed to its superior non-linear interpolation and denoising capabilities. The MSE performance gap between SRIR-ChNet and CAE-ChannelNet is 13.6dB and 11dB with GAN-CBD under 180 elements as shown in Figure 4. 27.

4.4.2.3 MSE vs. Number of Antennae

In this section, we investigate the relationship between the Mean Squared Error (MSE) of channel estimation and the number of antennas in RIS-MIMO systems. The Figures illustrate how varying the number of antennas impacts MSE under different signal-to-noise ratio (SNR) conditions.

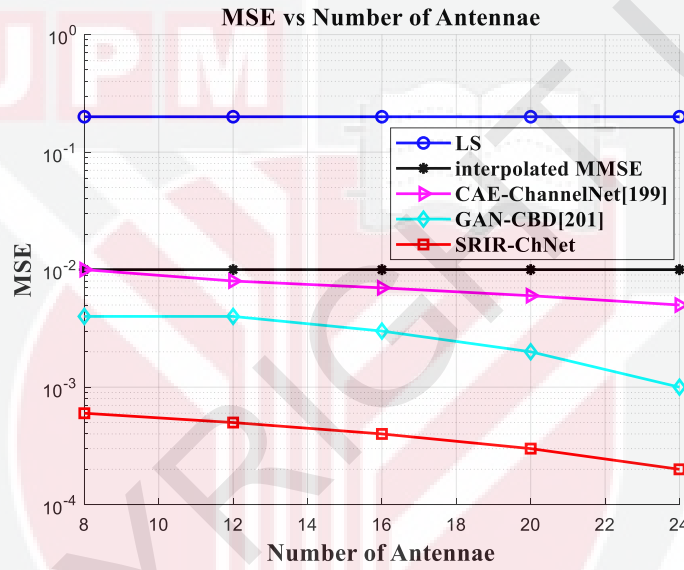


Figure 4.28: MSE performance for the channel under SNR = 10dB, and 8 pilots

The number of antennas, denoted N_{BS} , determines the channel dimension and impacts estimation performance. Consequently, we investigated the MSE performance as N_{BS} increases, presenting the results in Figure 4.28. Notably, the MSE of analytical channel estimators (LS and interpolated MMSE) remains constant irrespective of N_{BS} , whereas the MSE of the DL-based estimators changes with the number of antennas, i.e., the CAE-ChannelNet, GAN-CBD, and SRIR-ChNet decrease. This is because, in the simulation, we separately estimate the channels of each antenna and average their performance. The behavior of DL-based estimators differs because they process input

signals from all N_{BS} antennas simultaneously. As N_{BS} increases, these estimators benefit from both a larger input feature set and increased overall signal energy relative to noise, resulting in a lower MSE. Within this category of estimators, SRIR-ChNet demonstrates superior performance, achieving the minimum MSE.

4.4.2.4 MSE vs. SNR

In this section, we examine the connection between channel estimation MSE and SNR within RIS-MIMO systems. The Figures provide insights into how varying SNR levels impact MSE under different conditions, highlighting the importance of SNR in achieving accurate channel estimation.

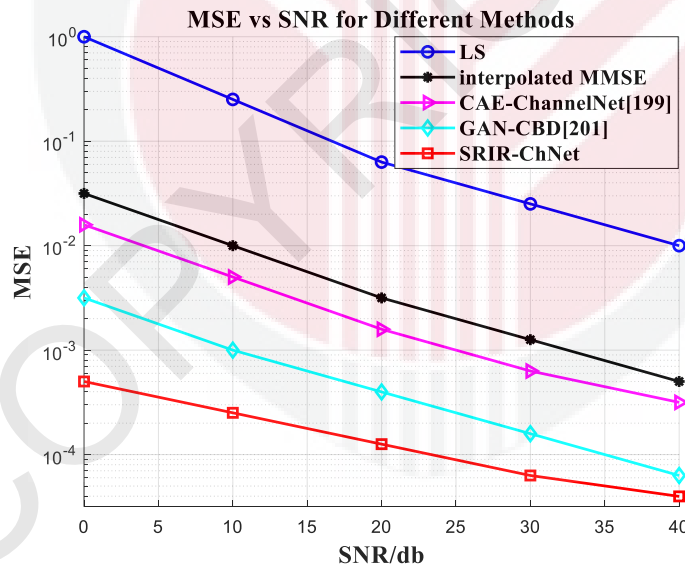


Figure 4.29: Performance comparison of different algorithms when the number of pilots is 8

Then, we evaluate the efficiency of various channel estimation methods. Our SRIR-ChNet is juxtaposed against four techniques mentioned in [199][201]: namely, least square (LS), interpolated minimum mean square error (interpolated MMSE),

generative adversarial network (GAN-CBD), and CAE-ChannelNet. Figure 4.29 displays the cascaded channel MSE versus SNR. The performance of all estimators enhances (MSE lowers) at higher SNRs due to the reduced effect of noise. Based on these results, we next analyze the conventional and DL-based estimation methods individually.

First, we evaluate the estimation performance of the LS and Interpolation MMSE estimators using Mean Squared Error (MSE). The results clearly show that the Interpolation MMSE significantly outperforms the LS method. This advantage stems from Interpolation MMSE's ability to utilize second-order statistical knowledge of the channel. In contrast, the LS estimator treats unknown parameters as deterministic constants, operating without such prior knowledge. However, the LS estimator does improve its performance through noise reduction, achieved by discarding coefficients beyond the maximum channel length. Turning to the deep learning methods (CAE-ChannelNet, GAN-CBD, and SRIR-ChNet), we observe that CAE-ChannelNet's performance is comparable to that of GAN-CBD. This similarity arises partly because both methods essentially function as denoising models applied to the initial LS estimate. Additionally, CAE-ChannelNet's performance might be constrained as it is not trained end-to-end. In contrast, SRIR-ChNet takes a different route by learning a non-linear interpolation method, resulting in improved channel estimation accuracy and superior overall performance compared to the other techniques. As illustrated in Figure 4.29, SRIR-ChNet demonstrates significant performance advantages. At an SNR of 10 dB, it achieves gains of 13 dB and 12 dB compared to CAE-ChannelNet and GAN-CBD, respectively. This superiority stems from SRIR-ChNet's ability to perform non-linear mapping from low-resolution to high-resolution channel

representations (akin to super-resolution) and learn distinctive noise features, which collectively enhance channel estimation accuracy. Consequently, SRIR-ChNet consistently provides the best channel estimation performance among the evaluated benchmarks. For example, when SRIR-ChNet reaches an MSE of -35 dB for the cascaded channel, it still maintains a 13 dB lead over CAE-ChannelNet and an 8 dB lead over GAN-CBD, highlighting its effectiveness.

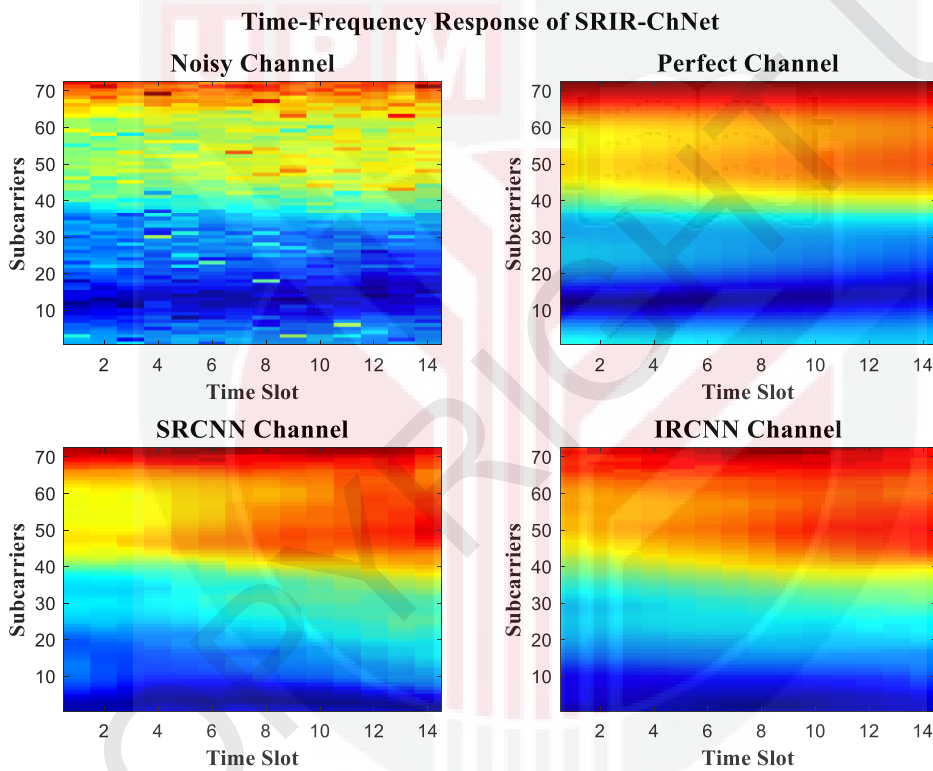


Figure 4.30: Output of SRIR-ChNet 2D image time-frequency response

The DnCNN is used for image denoising and is also referred to as IRCNN in some studies; both names refer to the same architecture. In the SRIR-ChNet model, the input is a 2D channel matrix that represents both perfect and noisy channels. The model is trained using the noisy channel as input, and its performance is evaluated by computing the mean squared error (MSE) between the estimated channel and the perfect channel.

Figure 4.30 shows the output of deep learning after applying the cascaded networks SRCNN and IRCNN. We trained the model on two types of channels: a noisy channel and a perfect channel, and then compared the model's output with the perfect channel to calculate the mean squared error (MSE) loss function. The results indicate that the output from the first network significantly improved the resolution of the noisy channel. Subsequently, when this output was fed into the second network, the noise was effectively reduced, resulting in an image with lower noise levels and higher resolution compared to the perfect channel.

4.4.3 Time Complexity Analysis

Further analysis involves determining the computational complexity of SRIR-ChNet. This requires examining its convolutional layers, whose parameters are detailed in Table 3.2. The time complexity for any given convolutional layer is determined by the formula:

$$C_{CL} = \mathcal{O}(\mathcal{W}_h \mathcal{W}_w F^2 N_I N_O), \quad (4.1)$$

where $\mathcal{W}_h$ and $\mathcal{W}_w$ as the output feature map height and width, F as the filter side length, N_I and N_O , indicate the input/output feature map counts, the overall complexity for SRCNN is consequently calculated as follows:

$$\begin{aligned} C_{SR} &= \mathcal{O}(2 \cdot N_{BS} \cdot N_P \cdot M(9^2 \cdot 2.64 + 1.64 \cdot 32 + 5^2 \cdot 32.2)) \\ &= \mathcal{O}(28,032 \cdot N_{BS} \cdot N_P \cdot M), \end{aligned} \quad (4.2)$$

Given N_p represents the pilots numbers per OFDM symbol and M total symbols per frame, the complexity associated with the IRCNN and its output layer is approximately:

$$C_{IR} = \mathcal{O}(2 \cdot N_{BS} \cdot N_p \cdot M(3^2 \cdot 2.64 + 3^2 \cdot 64.64.18 + 3^2 \cdot 64.2)) \quad (4.3)$$

$$\approx \mathcal{O}((816)^2 \cdot N_{BS} \cdot N \cdot M),$$

A fully connected layer has a time complexity of

$$C_{FC} = \mathcal{O}(I_x I_y N_{FC}), \quad (4.4)$$

where I_x and I_y signify the input dimensions, and N_{FC} as the number of fully connected layer units. Based on these parameters, the complexity of the fully connected layers can be approximated.

$$C_{FC} \approx \mathcal{O}(2 \cdot N_{BS} \cdot N \cdot M \cdot 128), \quad (4.5)$$

$$= \mathcal{O}(256 \cdot N_{BS} \cdot N \cdot M),$$

The number 128 is the fully connected units in the dense layer. The overall time complexity for the SRIR-ChNet is:

$$C = C_{SR} + C_{IR} + C_{FC}$$

$$= \mathcal{O}(((816)^2 + 256) \cdot N_{BS} \cdot N \cdot M + 28,032 \cdot N_{BS} \cdot N_p \cdot M), \quad (4.6)$$

The time complexity of both the concrete and interpolation layers can be analyzed because the interpolation method is formulated as a convolutional layer as:

$$C_{In} = \mathcal{O}(2 \cdot N_{BS} \cdot N_p \cdot M(4^2 \cdot 2.64)) \quad (4.7)$$

$$C_{Co} = \mathcal{O}(2 \cdot N_{BS} \cdot N_p \cdot M(3^2 \cdot 3.64)) \quad (4.8)$$

The total time complexity of CAE-ChannelNet [199] is:

$$\begin{aligned} C &= C_{SR} + C_{Dn} + C_{In} + C_{Co} \\ &= \mathcal{O}(((816)^2 + 256) \cdot N_{BS} \cdot N \cdot M + (28,032 + 7552) \cdot N_{BS} \cdot N_P \cdot M) \end{aligned} \quad (4.9)$$

The time complexity of the training phase in GAN-CBD [201] is:

$$\mathcal{O}(N^2 K^2 s t (L_{g,d} D_{g,l}^2 + L_{g,e} E_{g,l}^2 + L_a E_a^2)), \quad (4.10)$$

Where s donates the size of the mini-batch, t donates the number of iterations, K^2 , donates the size of kernels. $L_{g,e}$, $L_{g,d}$, and L_a , denote the number of “Conv” for DNN_D , DNN_E , and DNN_a , $D_{g,l}$, $E_{g,l}$ and E_a , denote the number of features for the l th layer of DNN_D , DNN_E , and DNN_a , respectively.

It is obvious that $C_{In} + C_{Co} > C_{FC}$. The SRIR-ChNet demonstrates superior computational efficiency with an average execution time of 0.86×10^{-2} s. This is significantly faster than both CAE-ChannelNet [199] is 7.18×10^{-2} s and GAN-CBD [201] is 9.8×10^{-2} s. It also the traditional interpolated MMSE and LS estimators, which require 2.12×10^{-2} s $\mathcal{O}(N_{BS} \cdot (N \cdot M)^3)$ and 4.01×10^{-2} s $\mathcal{O}(N_{BS} \cdot N \cdot M)$ [254], respectively.

We measured these runtimes using a desktop PC featuring an Intel i9-12900H (3.30 GHz) CPU, 32 GB RAM, and an Nvidia GeForce RTX 3070 Ti GPU.

Table 4.3: Runtime Analysis of Estimation Algorithms

Method	Prediction Time
LS	4.01×10^{-2} s
interpolated MMSE	2.12×10^{-2} s
CAE-ChannelNet [199]	7.18×10^{-2} s
GAN-CBD [201]	9.8×10^{-2} s
SRIR-ChNet	0.86×10^{-2} s

The reduction in prediction time, as shown in Table 4.3, is primarily due to several factors. The experiments for all methods were performed on a desktop PC featuring an Intel i9-12900H (3.30 GHz) processor and an Nvidia GeForce RTX 3070 Ti graphics processing unit (GPU). the use of an optimized model with reduced complexity, enabling faster computations; the application of parallel processing techniques, particularly leveraging GPU acceleration; and the use of preprocessing methods like channel sparsity and dimensionality reduction, which reduce the amount of data processed. These factors collectively contribute to the observed reduction in prediction time.

4.5 Performance Evaluations for Cascaded and Separate Channel Estimation using PSBA-H in RIS-MIMO System

This section assesses and validates the cascaded and separate channel estimation technique of the proposed PSBA-H in the uplink/downlink RIS-MIMO system. Their performance is compared with DDL and DQN [126]. In this objective, our proposal is a deep learning approach operating on two time scales for optimizing phase shifts and beamforming (PSBA-H) design in a time-varying RIS-MIMO system.

4.5.1 Simulation Setup and Parameter Specifications

We consider a system consisting of two base stations equipped with N antennas, one RIS with K_{active} and $K_{passive}$ elements, two controllers for cascaded scenarios, and two UEs. Let $H_{T,K} \in C^{N \times K}$ denote the channel from BS to RIS. Since the BS and the RIS are at fixed locations, the distance =100m, we assume that $H_{T,K}$ is a static channel. Let $H_{K,R} \in C^{K \times M}$ denote the reflected channel from RIS to UE, time-varying, and the

distance =100m. It is assumed that users are randomly dispersed and slowly move within a circle with a 10-meter radius, a direct connection between the BS and UE is obstructed, all the channels are Rician fading with Rician factor as $K_{k,n} = 10$ dB, and three bits are used to quantize the phase shifts at every RIS element. We use MATLAB 2023a for modeling the channels and to implement deep learning we used an Intel Core i9-12900H 3.30 GHz CPU and an Nvidia GeForce RTX 3070Ti GPU through the Anaconda, Spyder-based TensorFlow, and Keras libraries. The training rate is set at 0.001 and the batch size is 128. The training, validation, and testing sets include 30,000, 5,000, and 5,000 samples, respectively. The summary of the simulation parameter values considered for the RIS-MIMO system are the 5G propagation environment standards and are given in Table 4.4 and most of them are obtained from [126].

Table 4.4: The parameter setup for the RIS scenario

Parameters	Values
MIMO, RIS, BS, UE	2 x 2, 1,2,2
Distance between RIS-BS	100m
Distance between RIS-UE	100m
Simulation	Uplink/Downlink
RIS Controller BS	BS1,BS2
Distance between users and BS	102m
Pathloss of the Links	BS1:RIS1*60,RIS1:UE1*110 BS2:RIS2*60,RIS2:UE2*110
Reflect Coefficient of RIS	1
Width of the RIS Elements	0.012m
Length of the RIS Elements	0.012m
No.of RIS Elements	{8,80}
Modulation type	OFDM 64 QAM
Maximum Doppler frequency	36 Hz, 200 Hz
Channel model	Gaussian Noise
Sample frequency	3.84 MHz
No. of Sub-carriers	72
Time Slot	14
Fading	Rician
Frame Structure	TDD/FDD
Channel Power Delay Profile	PedestrianA
Channel Estimation Method	Pilot Aided LS
Pilot Pattern Downlink	Diamond

4.5.2 Simulation Results

This section presents the simulation results and evaluation performance of the proposed PSBA-H-based cascaded and separate channel estimation in RIS-MIMO in comparison with the existing techniques [126]. The performance evaluation is carried out in terms of some measurement metrics such as Normalized path loss, Channel Gain, Capacity, NMSE, Data Rate, Pilot Overhead, and Time Complexity. The simulation is performed using a MATLAB simulator.

4.5.2.1 Capacity vs. SNR

In this section, we investigate the connection between signal-to-noise ratio (SNR) and channel capacity for cascaded and separate channel estimation techniques, confirming that higher SNR yields greater capacity. In cascaded channel estimation, multiple links are involved, allowing for enhanced spatial diversity and coherent combining of signals. This leads to improved channel state information (CSI) and higher effective capacity as SNR increases. In contrast, separated channel estimation focuses on individual links without leveraging the benefits of multiple paths. While it may require more pilots and incur higher pilot overhead, it often results in reduced capacity compared to cascaded systems because it does not fully exploit spatial diversity or coherent signal combining. Empirical results, such as those illustrated in Figures 4.31 and 4.32, show that as SNR increases, cascaded channel estimation consistently outperforms separated channel estimation, DDL, and DQN [126] in terms of capacity.

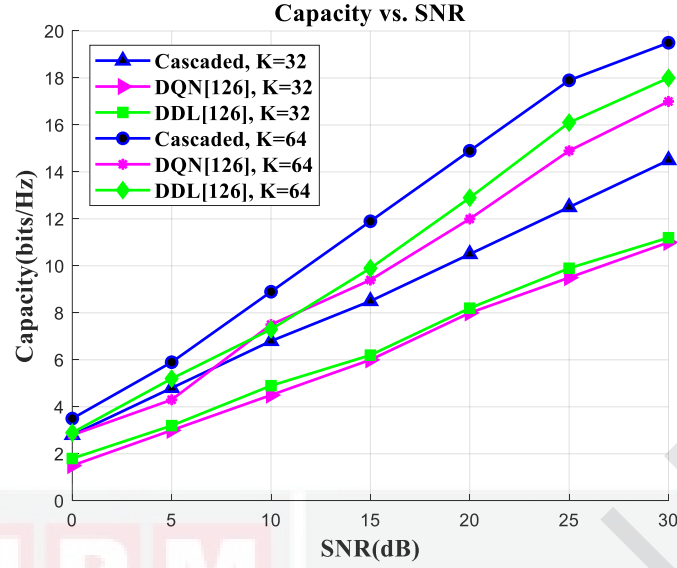


Figure 4.31: The comparison of capacities in the RIS-MIMO system, for proposed downlink cascaded, double deep learning (DDL) [126], and deep-Q-network (DQN) [126] channels with K=32 and 64 elements

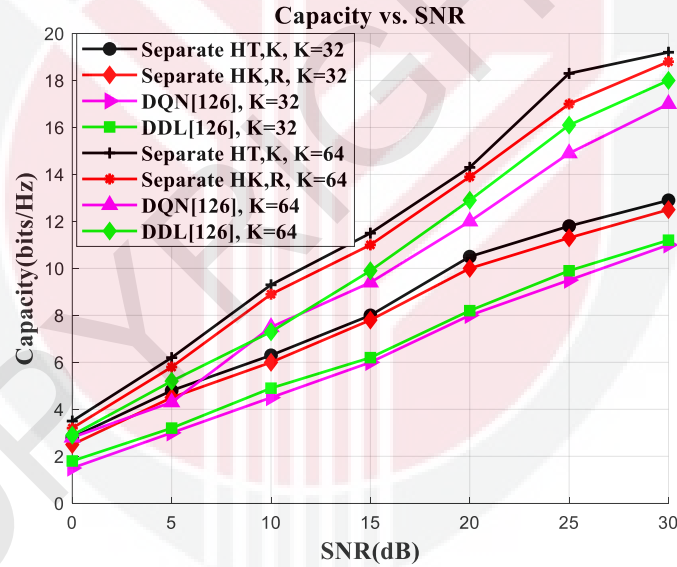


Figure 4.32: The comparison of capacities in the RIS-MIMO system, for proposed uplink/downlink separate, double deep learning (DDL)[126], and deep-Q-network (DQN)[126] channels with K=32 and 64 elements

Figures 4.31 and 4.32 show the capacities for cascaded and separated channels within an RIS-MIMO system configured with two source and two destination antennas. The results for the RIS element numbers $K = 32$ and 64 are presented. A total of 40,000 training datasets were generated to train the networks Net1 and Net2, following the

procedures outlined in Chapter Three. The proposed approach demonstrates a higher capacity than the DDL [126]. A comparison is also made with the Deep Q-Network (DQN) [126], a standard reinforcement learning approach. Results show that DQN performs similarly to DDL when $K = 32$ and $K = 64$. This comparable performance indicates that reinforcement learning methods like DQN are ill-suited for this problem, especially as the RIS size increases, which drastically expands the action space and hinders DQN's ability to converge. The proposed algorithm outperforms other algorithms in terms of capacity. This is because we apply a Brute Force Search (BFS) algorithm to evaluate the phase shifts for each RIS element, assuming that the phase shifts are discrete with three R -bits quantization. Given this, each RIS element will have 2^R possible phase shifts. The BFS algorithm will evaluate all possible combinations of phase shift levels $\Theta(t)$ across the RIS elements after training Net1 and optimal beamforming $W(t)$, from Net2, which are jointly optimized from the loss function to maximize the channel capacity. The fully passive RIS also has the best performance compared to all the semi-passive RIS setups. Since we estimate the two individual channels separately, the performance degradation may come from sharing the total training overhead and fewer RF chains at the RIS. Additionally, PSBA-H has the advantage of end-to-end optimization, where the entire network is trained. In contrast, the deeper models (DDL) suffer from overfitting and slow convergence in complex scenarios like RIS-MIMO. PSBA-H, with its well-structured design for capturing channel characteristics, can give a better data rate by avoiding overfitting and achieving faster convergence. While, DQN which is typically based on reinforcement learning, is less effective in continuous optimization problems such as channel estimation, especially when the reward structure is not as well-defined for data rate maximization.

4.5.2.2 Normalized path loss vs. Observation angle

This section presents the normalized path loss (in dB) that varies as a function of the observation angle (θ_s) for different sizes of meta-atoms in a Reconfigurable Intelligent Surface (RIS). Specifically, the meta-atom sizes are given as multiples of the incoming wavelength $a=\lambda$, $a=4\lambda$, $a=\lambda/2$, and $a=\lambda/5$. Figure 4.33 and Figure 4.34 illustrate the performance of normalized path loss at different observation angles. The path loss remains relatively constant across all observation angles when $a = \lambda$, this indicates that when the meta-atom size is equal to the wavelength, the path loss is modestly affected by the observation angle. When $a=4\lambda$ the path loss decreases significantly as the observation angle increases, which suggests that when the meta-atom size is much larger than the wavelength, the path loss is highly sensitive to the observation angle.

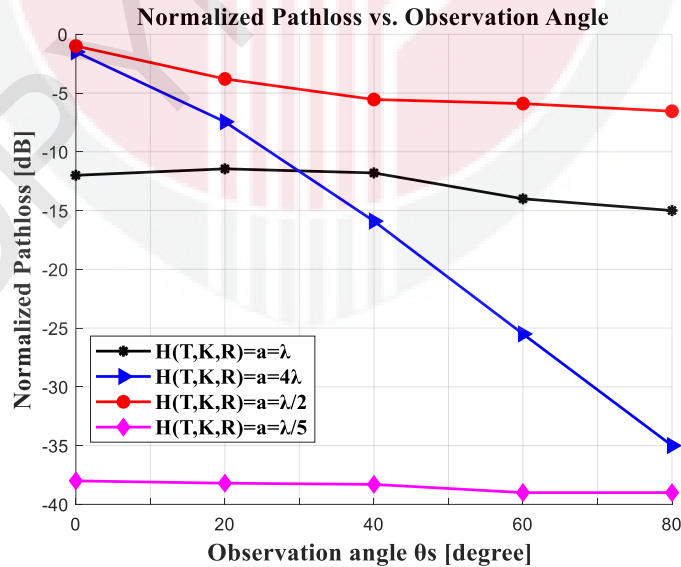


Figure 4.33: The normalized path loss for cascaded channels when the size of (Meta-atom a) is equal to 4λ , λ , $\lambda/2$, and $\lambda/5$ incoming wavelengths with different degrees of angle θ_s

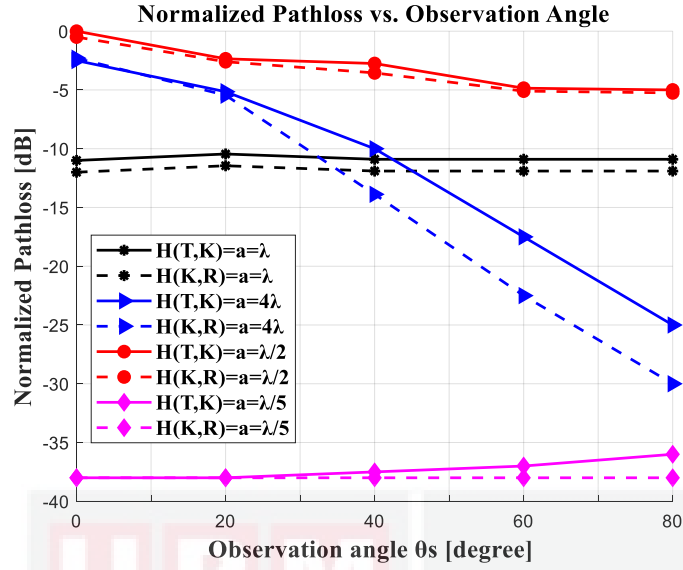


Figure 4.34: The normalized path loss for separate channels when the size of (Meta-atom a) is equal to 4λ , λ , $\lambda/2$, and $\lambda/5$ incoming wavelength with different degrees of angle θ_s

The performance degrades quickly as the angle increases. In the case of $a=\lambda/2$, the path loss is relatively stable but slightly decreases as the observation angle increases. This shows that reducing the size of the meta-atoms to half the wavelength maintains a stable path loss across the angles, but with a slight overall loss. While $a=\lambda/5$, the path loss is the lowest across all observation angles. This suggests that when the meta-atom size is much smaller than the wavelength ($\lambda/5$), the path loss remains minimal and almost unaffected by the observation angle. The best value in the figure is achieved when the meta-atom size is smallest relative to the wavelength ($a=\lambda/5$). This is justified as the best value because the path loss is consistently low across all observation angles, indicating efficient signal reflection and reduced attenuation. The path loss remains nearly constant across all angles, which means the RIS can effectively maintain the signal strength irrespective of the direction of the incoming wave. This is particularly advantageous in practical scenarios where the angle of incidence might vary. Conversely, larger meta-atom sizes, such as 4λ , result in higher angle-dependent path loss, reducing the effectiveness of the RIS in controlling the reflected signal.

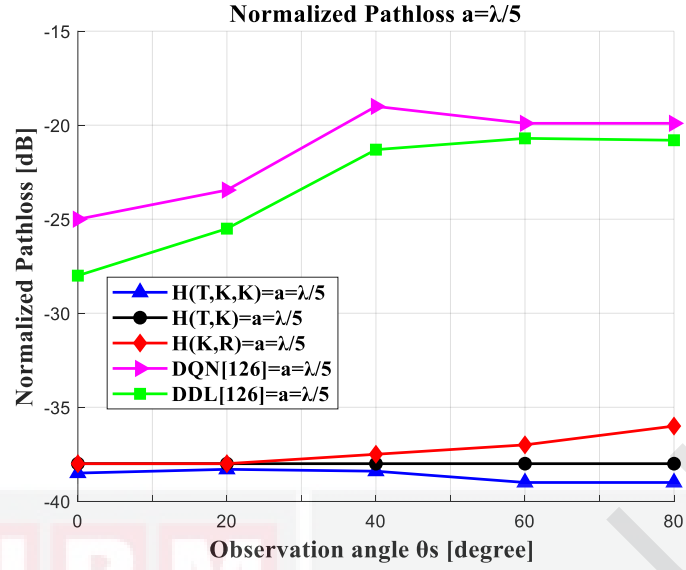


Figure 4.35: The normalized path loss for cascaded and separate channels when the size of (Meta-atom a) is equal to $\lambda/5$ incoming wavelength with different degrees of angle θ_s

Figure 4.35 illustrates the normalized path loss across various observation angles for different RIS-MIMO configurations, with a meta-atom size of $a=\lambda/5$. The proposed configurations $H_{T,K,R}$, $H_{T,K}$, and $H_{K,R}$ maintain low and stable path loss values across all angles, demonstrating their robustness to changes in the direction of incoming signals. This stability indicates that these methods effectively manage signal reflection, minimizing attenuation and making them suitable for real-world scenarios where the angle of incidence may vary. In contrast, the benchmark methods DQN and DDL exhibit significantly higher path loss, which increases with the observation angle, especially beyond 20° . This sensitivity to angle variation highlights their reduced efficiency in preserving signal strength, which limits their effectiveness in dynamic environments. The proposed methods' ability to maintain stable path loss at all angles is attributed to the optimized phase shift and beamforming design, which enables better control over signal reflection, underscoring their suitability for reliable RIS-MIMO communication systems.

4.5.2.3 Total Channel Gain vs. Distance

This section presents the total channel gain in a Reconfigurable Intelligent Surface communication system that is significantly influenced by the distances between the source and destination relative to the RIS. As the distance increases, the channel gain typically decreases due to increased path loss.

The total channel gain reaches its maximum when the RIS is positioned directly at the source or the destination, minimizing the propagation distance. This is because the path loss is minimized when the RIS is positioned very close to either the transmitter (source) or receiver (destination), resulting in a stronger reflected signal that significantly enhances the channel gain. As the distance d_l between the RIS and either the source or the destination increases, the total channel gain correspondingly decreases.

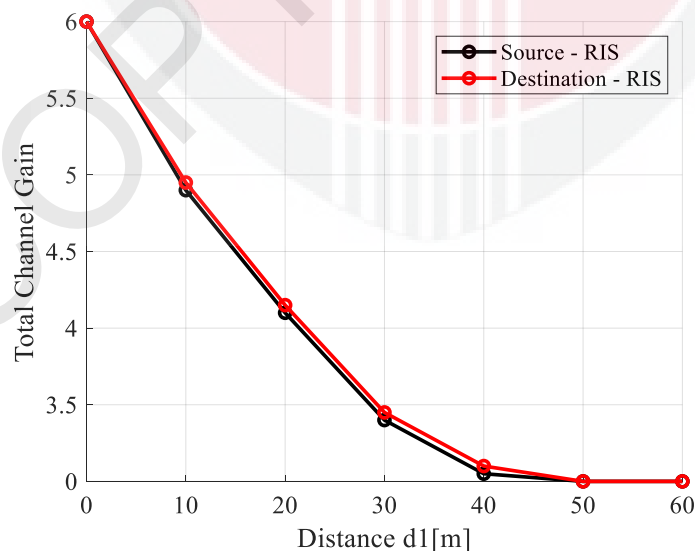


Figure 4.36: The total channel gain depends on the distance of the source and destination from the RIS

This suggests that the positioning of the RIS is symmetrically impactful, whether it is placed closer to the source or closer to the destination. The total channel gains benefit equally from proximity to either side of the communication link. The main factor influencing this behavior is the inverse-square law of signal propagation, where the power of a signal diminishes proportionally to the square of the distance it travels. The closer the RIS is to either the source or destination, the less path loss occurs, and the stronger the reflected signal remains. This results in a higher channel gain when the RIS is near one of the nodes, as seen in Figure 4.36. Conversely, as the RIS moves further away, the signal experiences greater attenuation, and thus the channel gain reduces significantly.

4.5.2.4 Data Rate vs. Number of RIS Elements

This section illustrates how the data rate (in bits/s/Hz) varies with the number of Reconfigurable Intelligent Surface (RIS) elements, comparing scenarios with and without RIS assistance under Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. Figure 4.37 presents the simulation results used to evaluate signal focusing, allowing us to compare the difference between Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) scenarios for both baseline and RIS. Then we calculated the amount of data rate. The black dashed line represents the baseline performance, which is the data rate without the presence of RIS elements. The red line indicates the data rate with RIS, and it increases as the number of RIS elements increases. The improvement of the data rate with RIS demonstrates the effectiveness of the RIS in enhancing the signal quality and performance of the wireless link. Direct Path (LOS, -75 dB): In the scenario with a Line-of-Sight path (typically represented by minimal obstruction), the

path loss is around -75 dB. In this case, the data rate is relatively high even without the RIS, and the impact of adding RIS elements is less significant, as seen by the slight increase in the red line above the baseline. Indirect Path (NLOS, -100 dB): In the Non-Line-of-Sight scenario, there is significant path loss (about -100 dB) due to obstacles or multipath effects that obstruct the direct path between the source and the destination. Here, the data rate without RIS is significantly lower.

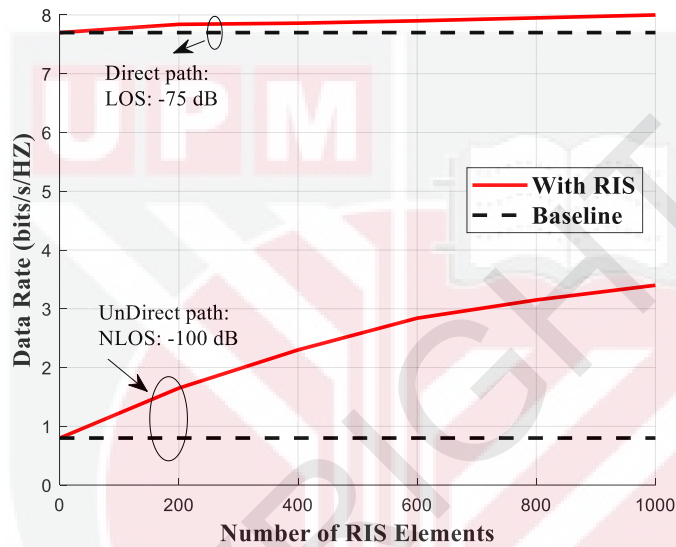


Figure 4.37: Illustrates the path LOS and NLOS with RIS and the direct path

However, increasing the number of RIS elements leads to a substantial improvement in the data rate, as the RIS effectively compensates for the NLOS condition by reflecting the signal in a controlled manner. The figure shows that as the number of RIS elements increases, the data rate improves for both LOS and NLOS scenarios. The improvement is more pronounced for the NLOS case, where the RIS effectively provides an alternative path for signal reflection, thus overcoming the limitations caused by obstruction or poor signal propagation. The greater the number of RIS elements, the better the control over the signal reflection, leading to an increase in signal strength at the receiver and hence a higher data rate. For the LOS scenario, the

improvement in the data rate with an increasing number of RIS elements is relatively small. This is because the direct path is already strong, and the RIS provides only marginal enhancement. The red line asymptotically approaches a maximum value of around 8 bits/s/Hz, indicating that beyond a certain number of RIS elements, the benefit in terms of data rate becomes negligible. The figure suggests that placing RIS elements in environments with significant NLOS conditions can greatly improve communication performance.

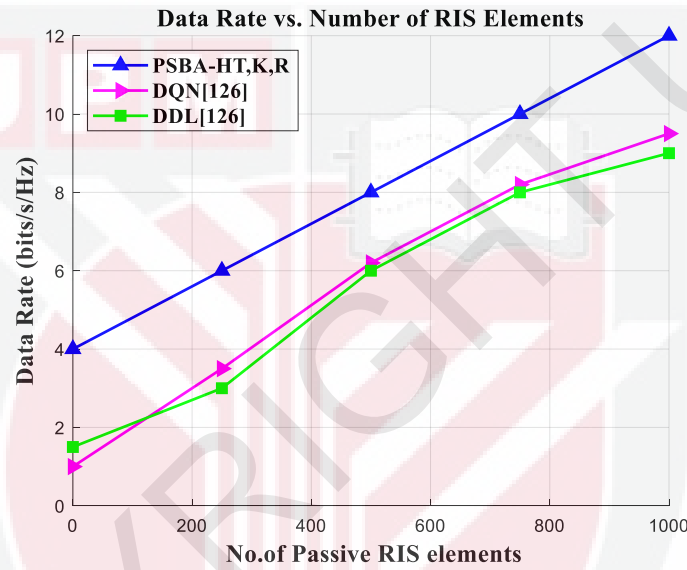


Figure 4.38: Data rate performance compared with DQN and DDL [126] using downlink cascaded scenarios

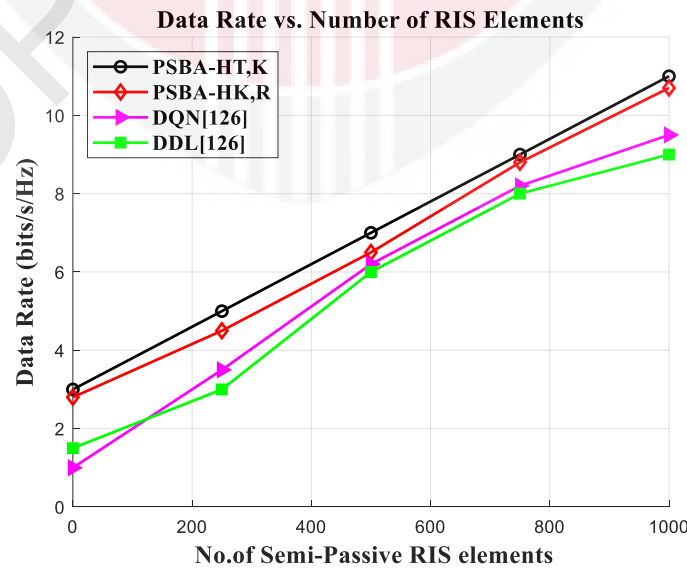


Figure 4.39: Data rate performance compared with DQN and DDL [126] using uplink/downlink separate scenarios

Figures 4.38 and 4.39 depict the relationship between the data rate and the number of RIS elements K . As K increases, both the cascaded and separated systems achieve higher data rate gains; however, the performance improvement for the cascaded system is significantly larger than that for the separated, DQN, and DDL [126]. For instance, when K increases from 0 to 1000, the data rate of the passive RIS-MIMO system increases from 4.23 bps/Hz to 12.44 bps/Hz. While the semi-passive RIS-MIMO system shows a data rate increase from 2.59 bps/Hz to 11.91 bps/Hz, it's still lower than cascaded channels. It is important to note that this comes at a higher power consumption cost due to the active amplification required for each element. Note that for $K = 9000$ and 1000 , the DQN and DDL methods yield poor results that are difficult to obtain. This is due to the significant scale of the problem, involving complexities on the order of $2^{3 \times 900} = 2^{2700}$ or $2^{3 \times 1000} = 2^{3000}$ possible phase shifts for every set of channel realizations to go through, respectively. These results suggest that the passive RIS-MIMO system achieves higher data rates and offers a more energy-efficient solution with lower power consumption per element, making it a better choice for scenarios where energy efficiency is critical.

4.5.2.5 NMSE vs. SNR

This section illustrates a comparison of the NMSE performance among different structures of the proposed PSBA-H-based cascaded and separate channel estimators with methods in benchmark DQN and DDL [126].

Figure 4.40 compares the performance of PSBA-H-based methods with DQN and DDL [126] in terms of normalized mean square error (NMSE) for different signal-to-

noise ratios (SNR). The proposed PSBA-H algorithms show better performance than DQN and DDL. This is because PSBA-H includes an optimal phase shift and beamforming strategy that directly enhances the received signal quality. Optimizing both phase shifts and beamforming allows more effective mitigation of the random effects introduced by the channel, resulting in more accurate channel estimates.

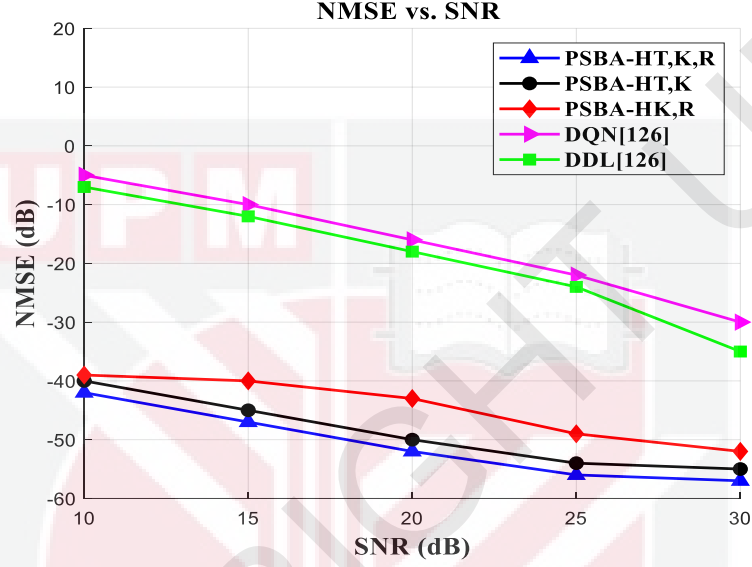


Figure 4.40: The NMSE performance among Cascaded, Separate, DQN, and DDL [126]

Since CNNs are particularly good at extracting spatial features, they can be highly beneficial in RIS-MIMO systems where spatial correlation plays a significant role in signal transmission and reflection. The PSBA-H likely leverages this feature extraction capability to achieve better channel estimation accuracy.

4.5.2.6 Pilot Overhead vs. Number of RIS Elements

In this section, We illustrate the connection between the required pilot overhead and the RIS size (number of elements) for both cascaded and separated channel estimation

methods with the number of RIS elements and compare the results with the methods in the benchmark [126].

In the quasi-static (BS-RIS) channel estimation, there are $(K + 1)$ sub-frames, each consisting of L time slots. Taking the least value $L = 2$, the associated pilot overhead is $\tau_1 = (K + 1) L = 2(K + 1)$. In the mobile channel estimation (RIS-UE), there are $\tau_{min} = \lceil \frac{K}{N} \rceil$ sub-frames, each of which consists of M time slots, so the pilot overhead for RIS-UE the mobile channel estimation is $\tau_2 = M \lceil \frac{K}{N} \rceil$. The quasi-static BS-RIS channel is estimated in a large timescale in the proposed two-time channel estimation framework. As a result, we must average the pilot overhead for large-scale channel estimation, depending on the frequency at which the BS-RIS channel is estimated. Specifically, let T_L and T_S represent the channel coherence times for the large-timescale and small-timescale channels, respectively, with $T_L = \alpha T_S$, where $\alpha \gg 1$. Throughout T_S , the average pilot overhead is calculated as $\tau = \frac{T_S}{T_L} \cdot \tau_1 + \tau_2 = \frac{2(K+1)}{\alpha} + M \lceil \frac{K}{N} \rceil$. The pilot overhead of the proposed two scenarios for channel estimation is lower than $(N + K)M$, as compared to DDL [126], and also lower than $M + K + \max\{M - 1, \lceil \frac{(M-1)K}{N} \rceil\}$ DQN in [126] when $\alpha > 2$. Then, we compare the pilot overhead of different channel estimation schemes in Figures 4.41 and 4.42. It can be observed that the pilot overhead of the proposed PSBA-H channel estimation is lower than both the DDL channel estimation method [126] and significantly lower than the DQN method [126].

Figures 4.41 and 4.42 illustrate the pilot overhead against number of RIS elements across two different scenarios. In the cascaded scenario, the pilot overhead is relatively

low because we treat the two channels, $H_{T,K}$, and $H_{K,R}$ as a single channel. In contrast, the separate scenario demonstrates the worst performance due to the individual estimation of the two channels.

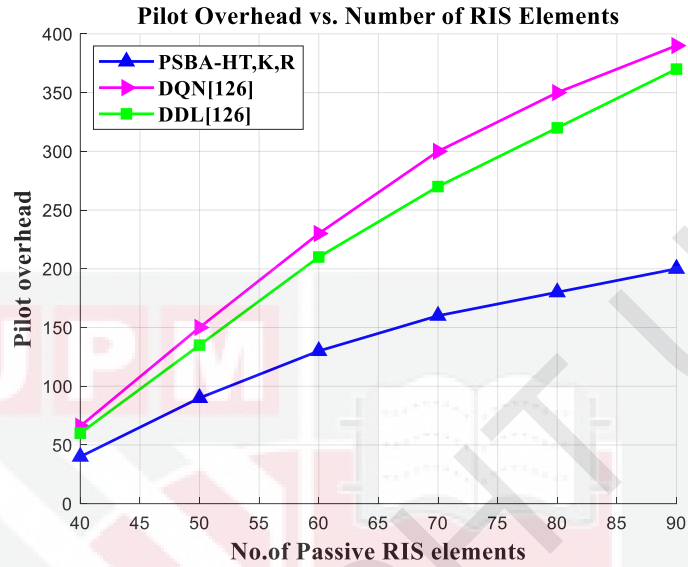


Figure 4.41: Pilot overhead vs. number of RIS elements in cascaded channels, where $N = 64$

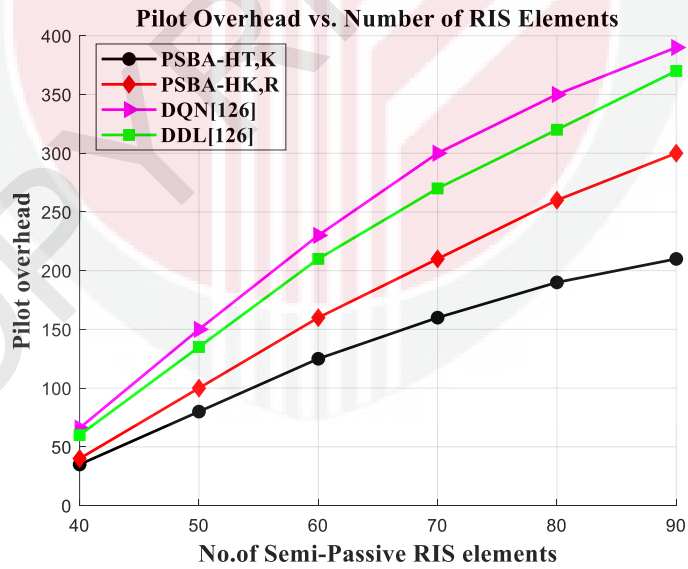


Figure 4.42: Pilot overhead vs. number of RIS elements in separate channels, where $N = 64$

The quasi-static channel from BS-RIS performs better than the mobile channel RIS-UE because the static nature and fixed position of the BS-RIS link allow for longer

timescale estimations, reducing the need for frequent channel updates. Conversely, the RIS-UE channel requires continuous estimation at shorter timescales due to user mobility, resulting in increased pilot overhead.

4.5.3 Time Complexity Analysis

We investigate the computational time required by PSBA-H. The standard calculation for a convolutional layer's time complexity involves the formula:

$$C_{CL} = \mathcal{O}(\mathcal{W}_h \mathcal{W}_w F^2 N_I N_O), \quad (4.11)$$

where $\mathcal{W}_h$ and $\mathcal{W}_w$ refer to the height and width of the output feature maps, FFF represents the filter's side length, and the number of input feature maps is represented by N_I and the number of output feature maps by N_O . Consequently, the total execution time for Net1 is calculated using the following expression:

$$\begin{aligned} C_{PSCNN} &= \mathcal{O}(2 \cdot N_{BS} \cdot N_P \cdot M(4^2 \times 2 \times 64 + 64 \times 4^2 \times 32 + 4^2 \times 64 \times 2)) \\ &= \mathcal{O}(71,680 \cdot N_{BS} \cdot N_P \cdot M), \end{aligned} \quad (4.12)$$

Where N_P indicates the number of pilots per OFDM frame, and the total count of symbols within a sub-frame is represented by M . Regarding the fully connected layer, its computational complexity is

$$C_{FC1} = \mathcal{O}(I_x I_y N_{FC}), \quad (4.13)$$

where I_x and I_y , represent the dimensions of the channel matrix, and N_{FC} , refers to the count of units within the fully connected layer. Hence, the complexity of the fully connected layers is an approximation.

$$C_{FC1} \approx \mathcal{O}(2 \cdot N_{BS} \cdot N \cdot M \cdot 128) \quad (4.14)$$

Where N are sub-carriers appended. Therefore, the total complexity for Net 1 is:

$$\mathcal{O}(C_{PSCNN} + C_{FC1}) \quad (4.15)$$

$$= (71,936) N_{BS} \cdot N \cdot M$$

$$C_{BACNN} = \mathcal{O}(2 \cdot N_{BS} \cdot N_p \cdot M (2 \times 3^2 \times 64 + 64 \times 3^2 \times 1 + 1 \times 3^2 \times 32 + 32 \times 3^2 \times 2)) \quad (4.16)$$

$$= \mathcal{O}(5,184 \cdot N_{BS} \cdot N_p \cdot M),$$

The fully connected layer's computational complexity is

$$C_{FC2} = \mathcal{O}(I_x I_y N_{FC}) \quad (4.17)$$

$$C_{FC2} \approx \mathcal{O}(2 \cdot N_{BS} \cdot N \cdot M \cdot 128), \quad (4.18)$$

Thus, the total complexity for Net 2 is dominated by the matrix operations and can be approximated as:

$$\mathcal{O}(C_{BACNN} + C_{FC2}) \quad (4.19)$$

$$= \mathcal{O}(5,440 \cdot N_{BS} \cdot N_p \cdot M),$$

The total time complexity of the proposed algorithm is

$$= (71,936 + 5,440) \cdot N_{BS} \cdot N_p \cdot M \quad (4.20)$$

$$= (77,376) \cdot N_{BS} \cdot N_p \cdot M \text{ operations.}$$

The experiments for all methods were conducted using a desktop PC powered by an Intel i9-12900H 3.30 GHz CPU, which provides high processing power for complex computations, and an Nvidia GeForce RTX 3070Ti GPU. For your Intel i9-12900H

CPU (which has 6 cores and a base clock speed of 3.30 GHz) and Nvidia GeForce RTX 3070Ti GPU, the execution time would be calculated for total operations: 6 cores $\times$ 3.30 GHz $\times$ 16 FLOP/cycle 316.8 G FLOPS.

Time (seconds) $=\frac{2,379,776,000}{316.8 \times 10^9} = 0.0075$ seconds $\approx$ 7.5 milliseconds for cascaded channel.

Time (seconds) $=\frac{3,009,600,000}{316.8 \times 10^9} = 0.0095$ seconds and $\frac{2,914,560,000}{316.8 \times 10^9} = 0.0092$ seconds for Separate channels.

Time (seconds) $=\frac{40 \times 10^9}{316.8 \times 10^9} = 0.1262$ seconds for DDL and 0.2304 seconds for DQN.

Table 4.5: Time complexity for different estimation techniques

Method	Prediction Time
DDL [126]	0.1262 s
DQN [126]	0.2304 s
$PSBA - H_{T,K,R}$	0.0075×10^{-3} s
$PSBA - H_{T,K}$	0.0092×10^{-3} s
$PSBA - H_{K,R}$	0.0095×10^{-3} s

4.6 Performance Evaluation of all Proposed Channel Estimation Algorithms

The fourth objective of this thesis focuses on the performance evaluation of all the proposed channel estimation algorithms developed throughout objectives one, two, and three. This objective is critical as it comprehensively assesses the algorithms' effectiveness, robustness, and efficiency under various conditions. The evaluation is conducted using normalized mean square error (NMSE) against different signal-to-noise ratios (SNR). By benchmarking these algorithms against existing methods, the

study aims to highlight the improvements and limitations of each approach, offering valuable insights into their practical applicability in 5G and beyond communication systems. The results obtained from this evaluation will demonstrate the proposed methods' feasibility and superiority and guide future research directions in channel estimation. Figure 4.43 shows that Least Square (LS) has the highest NMSE across all SNR values, as shown by the blue line in the plot. LS is a traditional estimation method that does not exploit any prior knowledge of channel statistics or structure. It is susceptible to noise, which makes it perform poorly, especially at lower SNRs. While it does improve with increasing SNR, the NMSE remains significantly higher than the other methods because LS does not incorporate any advanced denoising or regularization techniques. Despite using a new method to arrange the pilot's pattern design, it remains less efficient than other deep learning algorithms. The proposed PSBA- $H_{T,K,R}$ model demonstrates superior performance over SRIR-ChNet, although both algorithms operate on the same communication system in cascaded downlink fully passive RIS-MIMO channel estimation, primarily due to its dedicated optimization of both phase shifts and beamforming. By employing PSCNN to fine-tune the RIS element phase shifts and BACNN to optimize beamforming, PSBA- $H_{T,K,R}$ ensure that the signals reflected by the RIS combine constructively at the receiver, maximizing signal quality and SNR. In contrast, SRIR-ChNet, while effective in denoising (IRCNN) and enhancing resolution (SRCNN), does not specifically optimize the key RIS parameters, such as phase shifts and beamforming, which are critical for leveraging the full potential of RIS in communication systems. Although both scenarios operate on the same communication system in separate semi-passive RIS-MIMO channel estimation, PSBA- $H_{T,K}$ performs better in the quasi-static

downlink scenario due to the stable channel conditions that allow for more effective phase and beamforming optimization, resulting in lower NMSE.

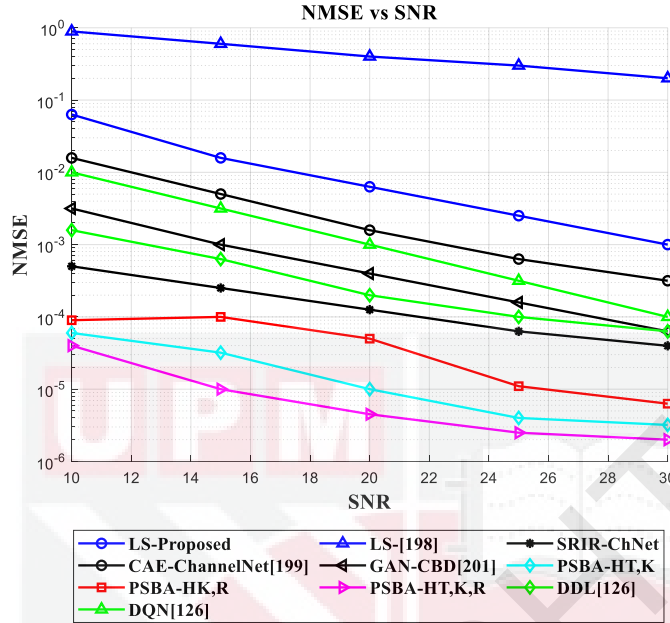


Figure 4.43: NMSE vs. SNR for all Proposed Channel Estimation Algorithms

On the other hand, PSBA-H_{K,R} is designed to handle the more dynamic time-varying uplink, where the active RIS elements help adjust to fluctuating conditions, albeit with slightly higher NMSE due to the channel's complexity. The use of PSCNN and BACNN in the active elements of the RIS further enhances both scenarios by providing real-time optimization, improving overall channel estimation performance.

4.7 Summary

This chapter demonstrated the simulation results by evaluating the performance of all the proposed channel estimation schemes. Initially, the performance evaluation of the LS estimator techniques using OFDM-RIS-MIMO for addressing the first objective, SRIR-ChNet for addressing the second objective in the downlink cascaded channel

estimation in RIS-MIMO system, was investigated, and the third objective investigated the PSBA-H scheme for cascaded and separate channel estimation in RIS-MIMO system. Then, the proposed techniques' results were compared with LS-based block [198], the least square (LS), interpolated minimum mean square error (interpolated MMSE), conditional generative adversarial network (GAN-CBD) [201], and CAE-ChannelNet in [199]. The least-square was considered to maximize the system sum rate, and SRIR-ChNet maximized system accuracy through its process of enhancing low-resolution images into high-resolution images. Furthermore, the type of channel estimation, as cascaded and separate, has also been considered for evaluation. The chapter has also investigated the performance of the distance between BS, RIS, and UE in terms of its achievable data rate. This is because the RIS-MIMO systems always favor placing the RIS closer to the BS or UE than a place far from them, which can help to achieve a high data rate. The normalized path loss for cascaded and separate channels was also investigated when the size of Meta-atom a is equal to $4\lambda, \lambda, \lambda/2$, and $\lambda/5$ incoming wavelength with different degrees of angle θ_s , we obtain the best performance when an equal to $\lambda/5$ and the worst case when an equal to $\lambda/2$. The results demonstrate that the PSBA- $H_{T,K,R}$ method achieves superior capacity in the downlink cascaded channel, reaching 14.3 bits/Hz with $K=32$ and nearly 20 bits/Hz with $K=64$ at 30 dB SNR, outperforming DDL and DQN [126]. In separate downlink and uplink channels, the PSBA-H methods maintain high capacities, achieving up to 19 bits/Hz and 18.5 bits/Hz, respectively. Additionally, PSBA-H methods significantly reduce computational time, with the cascaded channel taking 0.728 ms and separate channels 0.918 to 0.958 ms, compared to DDL at 0.1262 s and DQN at 0.2304 s.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

This thesis examined the channel estimation techniques in the uplink/downlink RIS-MIMO system. This chapter provides some concluding remarks and presents some possible future research directions.

5.1 Conclusion

Reconfigurable Intelligent Surfaces (RISs) have recently gained attention due to their significant potential in future 6G wireless communications, thanks to their low energy consumption and easy integration. However, the large quantity of inexpensive reflecting elements in RISs presents challenges for channel acquisition in various RIS-based wireless applications, such as RIS-enhanced orthogonal frequency-division multiplexing (OFDM) and multi-user multiple-input multiple-output (MU-MIMO) systems. With this concern, this thesis explored various channel estimation techniques intending to improve system data rate and accuracy, and also achieve fair and optimal channel state information performance for the uplink/downlink RIS-MIMO systems.

Starting by modeling the channel time-frequency response, generating a new dataset with 5G specifications as a 2D image using the PedA model in the MATLAB Link Level Simulator. This dataset consisted of 40,000 frames, with each frame containing four 2D images representing time-frequency responses. These frames were generated under various channel models, including AWGN, Rayleigh, and Rician, using 64-

QAM modulation techniques. The PedA model aimed to generate noisy channels, employing the least square (LS) channel estimation method with a diamond pilot pattern design for the downlink. The performance of RIS-MIMO downlink systems was studied without channel estimation, exploring different fast-fading channel models. Additionally, the LS channel estimation method's performance was evaluated by comparing the bit error rate (BER) and mean square error (MSE) for different modulation schemes, including 64-QAM, in AWGN, Rayleigh, and Rician channels. The simulation results have shown that the proposed LS addressed the first objective of the bit error rate performance between the Approximate-Perfect without channel estimation and pilot-aided LS channel estimation for all types of multipath fading. The results illustrated the effect of applying the LS estimator. The error happens in the case without the least square, which is 0.36 to 0.38 dB. The channel with LS showed a better performance in terms of bit error rate, and the minimum error occurred between 0.25 to 0.29 dB techniques, respectively. Then, the proposed technique results were compared with the LS-based block[198]. The proposed LS with a diamond pilot pattern reduces BER at 20 dB for AWGN, Rayleigh, and Rician by approximately 50%, 40%, and 33.33% compared to the traditional LS with a block pilot pattern.

Next, we model the channel between BS-RIS-UE as a 2D image-based resolution (SR) problem. This approach aims to improve the resolution and decrease the noise effect on the channel matrix, ultimately enhancing the system's accuracy. By applying super-resolution techniques, we can improve the resolution and clarity of the CSI, which in turn optimizes the overall performance of the communication system, which addresses the second objective. The channel response at the pilot positions was initially considered a low-resolution image, while the estimated channel response was

generated as a high-resolution image using the proposed method. We improved SRIR-ChNet-based DL (image super-resolution SRCNN and image restoration IRCNN techniques) to estimate the channel, enhances the resolution of the 2D time-frequency response channel matrix and effectively reduces noise by incorporating more hidden layers. As a result, it achieves superior accuracy in channel estimation, surpassing traditional methods. Additionally, it minimizes both mean square error (MSE) and time complexity, leading to more efficient and precise performance, the algorithm achieves superior performance, demonstrating its effectiveness in providing more reliable and precise channel estimation results. The results demonstrated the effectiveness of various channel estimation methods. Our SRIR-ChNet was compared with four techniques from [199][201]: least square (LS), interpolated minimum mean square error (interpolated MMSE), generative adversarial network (GAN-CBD), and CAE-ChannelNet. A standardized experimental framework was applied across all tests. The SRIR-ChNet consistently outperformed the traditional LS and MMSE methods, underscoring the advantages of deep learning approaches. As the SNR exceeded 15 dB, the estimation performance of all methods reached a point of stability. However, the results indicate that SRIR-ChNet achieves MSE values between 10^{-4} and 10^{-3} , outperforming CAE-ChannelNet MSE range: 10^{-2} to 10^{-1} and GAN-CBD MSE range 10^{-3} to 10^{-2} . Additionally, SRIR-ChNet has a total time complexity of 0.86×10^{-2} , which is lower than CAE-ChannelNet 7.18×10^{-2} and GAN-CBD 9.8×10^{-2} . The effectiveness of the proposed technique was assessed by benchmarking its results against established methods, including least square (LS), interpolated minimum mean square error (interpolated MMSE), conditional generative adversarial network (GAN-CBD) [201], and CAE-ChannelNet [199].

Finally, we developed a novel deep learning-based approach for channel estimation tailored to RIS-MIMO systems. This method is specifically designed to tackle the challenges posed by the integration of active and passive elements within the RIS, ensuring more precise and efficient channel estimation. Our method uses a two-stage channel estimation. The initial stage focuses on estimating the combined MIMO channel linking the Base Station (BS), RIS, and User Equipment (UE). In the second stage, we estimate the individual BS-RIS and RIS-UE channels separately. To optimize the estimation process, we propose two deep neural networks, PS-CNN and BA-CNN, which are referred to as Net 1 and Net 2, respectively. Net 1 is designed to address the complexity of phase reflection by optimizing the RIS phase shift matrix during the training phase. This optimization maximizes signal power and improves the SNR at the receiver. Meanwhile, Net 2 focuses on achieving optimal beamforming, thereby enhancing system capacity. The simulation results have shown the performance of the proposed in terms of normalized path loss, indicating that the best case is when the meta-atom size is $a = \lambda/5$, achieving the lowest and most stable path loss across all observation angles. The worst case occurs with $a = \lambda/2$, where path loss increases significantly and becomes highly sensitive to angle changes, reducing RIS effectiveness in maintaining signal strength for both scenarios. Then, the overall channel gain reaches its maximum when the reflective surface is positioned closest to either the source or the destination, meaning the distance between the RIS and the source or the RIS and the destination is zero. Following this, the signal focusing was analyzed to compare the performance of line-of-sight (LOS) and non-line-of-sight (NLOS) scenarios, as well as to evaluate the resulting data rate. In the first scenario, In a Line-of-Sight scenario with minimal obstruction, the path loss is approximately -75 dB. Here, the data rate is relatively high even without RIS, so the impact of adding

RIS elements is minimal, resulting in only a slight increase in performance. As for the second scenario, In a Non-Line-of-Sight scenario, significant path loss occurs (around -100 dB) due to obstacles or multipath effects. Without RIS, the data rate is considerably lower. However, a substantial increase in the number of RIS elements leads to a significant enhancement in the data rate as RIS compensates for NLOS conditions by reflecting signals effectively. The real difference becomes evident when using reflective surfaces, as the results show a higher data rate with the innovative reflected surfaces compared to regular surfaces for both cascaded and separate channels. Next, we compared the performance of PSBA-H-based methods with DQN and DDL[126] in terms of normalized mean square error (NMSE) across different signal-to-noise ratios (SNR). The PSBA-H algorithms outperform DQN and DDL due to their optimal phase shift and beamforming strategies, which enhance received signal quality. By optimizing both phase shifts and beamforming, PSBA-H effectively mitigates random channel effects, leading to more accurate channel estimates. CNNs excel at extracting spatial features, making them particularly beneficial in RIS-MIMO systems where spatial correlation is crucial for signal transmission and reflection. Thus, the PSBA-H leverages this capability to achieve superior channel estimation accuracy. The results show that the PSBA-H_{T,K,R} method for the downlink cascaded channel achieves superior capacity performance, reaching 14.3 bits/Hz at 30 dB SNR with $K=32$ elements, outperforming DDL (11.2 bits/Hz) and DQN (11 bits/Hz). For $K=64$ elements, capacity increases to nearly 20 bits/Hz, surpassing DDL (18 bits/Hz) and DQN (17 bits/Hz). In separate downlink channels, PSBA-H_{T,K} reaches approximately 19 bits/Hz with $K=64$ elements and 13 bits/Hz with $K=32$ at 30 dB SNR. Similarly, for separate uplink channels, the PSBA-H_{K,R} method achieves nearly 18.5 bits/Hz at 30 dB SNR with $K=64$ elements and 12.3 bits/Hz with $K=32$,

demonstrating significant improvements over DDL and DQN in both configurations. The results indicate that the proposed PSBA-H methods for both cascaded and separate channels significantly reduce computational time compared to DDL and DQN [126]. The PSBA-H method for the cascaded channel takes about 0.0075 seconds, while the separate channels range from 0.0092 to 0.0095 seconds. In contrast, DDL requires 0.1262 seconds, and DQN takes 0.2304 seconds.

5.2 Future Works

RIS holds significant potential for future advancements, with precise CSI being essential for optimal performance. However, channel estimation becomes significantly more complex in multi-RIS systems as the chain of cascaded links increases, reducing the effectiveness of techniques developed for single-RIS scenarios. Additionally, integrating RIS into higher frequency bands, such as the THz range, presents challenges due to signal propagation issues. In scenarios with significant mobility and potential obstructions, such as dense cities, areas with moving vehicles, or satellite systems, deploying RIS requires advanced channel estimation techniques to ensure stable and reliable communication. Combining deep learning algorithms with traditional schemes and leveraging deep learning's powerful data-fitting ability could greatly enhance the performance of existing methods and hold substantial promise. In summary, RIS offers immense potential and warrants further exploration. This thesis aims to provide valuable insights and foster the development of RIS, particularly in the evolving field of RIS channel estimation. This research aims to encourage further exploration of next-generation wireless communication technologies and their real-world applications. The key directions for future work are summarized as follows:

i. Double/Multi-RIS System

In wireless communication systems, Reconfigurable Intelligent Surfaces (RIS) are employed to enhance signal propagation by dynamically adjusting the reflection of electromagnetic waves. RIS elements can be either passive reflecting signals without amplification or actively capable of amplifying and processing signals. Accurate channel estimation is crucial for optimizing RIS performance. Utilizing two RIS elements, whether passive or active, can significantly improve the precision of channel estimation. This configuration enables the system to effectively capture and analyze the interactions between the transmitted signals and the environment, leading to more reliable communication. However, implementing dual RIS elements introduces complexities, such as increased computational requirements. With two RIS, the interactions between the surfaces can lead to interference that must be carefully managed to ensure optimal performance. The need for accurate channel state information (CSI) for both RIS increases the pilot overhead, requiring more resources for training and estimation processes, and the need for sophisticated algorithms to manage the interplay between the two surfaces. Additionally, active RIS elements, while offering greater control and amplification capabilities, come with higher energy consumption and potential hardware constraints. In summary, this increased complexity can lead to challenges in maintaining performance efficiency and may require advanced algorithms for effective management.

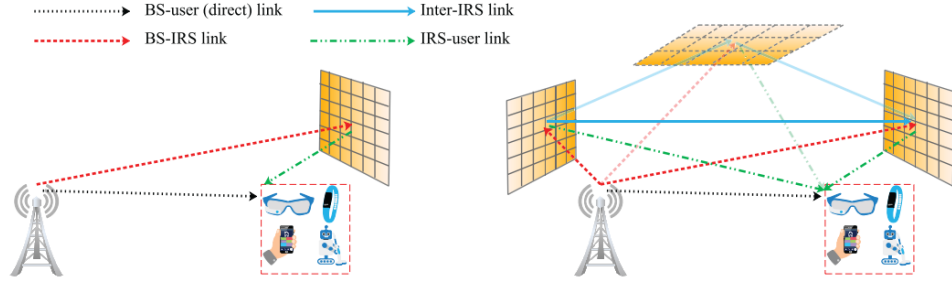


Figure 5.1: RIS-MIMO communication system with two RIS

ii. Hybrid/Combination of Separate and Cascaded Channel Estimation

One of the key limitations of this study is the inability to simultaneously apply both cascaded and separate channel estimation approaches. While it's not possible to directly combine the cascaded and separate approaches simultaneously, a hybrid channel estimation approach can be proposed. This scenario would allow the combination of the strengths of both methods under specific conditions. Instead of using cascaded or separate approaches individually, an adaptive mechanism could be developed that dynamically switches between the two methods based on environmental conditions and system requirements. This adaptive hybrid strategy would take into account factors such as mobility, signal-to-noise ratio (SNR), and hardware limitations to determine when to apply each approach. The transition between methods could be governed by a learning-based algorithm that optimizes the estimation process based on real-time system feedback. Another potential scenario could involve partitioning the RIS elements, where part of the RIS is used for separate channel estimation, while the rest is used for cascaded channel estimation. This division allows for a mixed utilization of resources, where complex individual link estimation is only applied where needed. The system can balance the trade-offs between accuracy, complexity, and energy consumption by dynamically switching

between cascaded and separate approaches. This would be particularly useful in scenarios where real-time adaptation is needed. This approach would reap the benefits of both methods the lower hardware cost and energy efficiency of cascaded estimation, and the high accuracy of separate estimation without committing fully to one method. In future work, it would be valuable to examine how combining the two techniques could improve channel estimation accuracy, particularly in scenarios involving different signal processing techniques, channel models, and hardware constraints. Exploring this integration could yield enhanced performance in terms of hardware cost, energy efficiency, and estimation accuracy, potentially providing a more optimal solution for RIS-enabled communication systems.

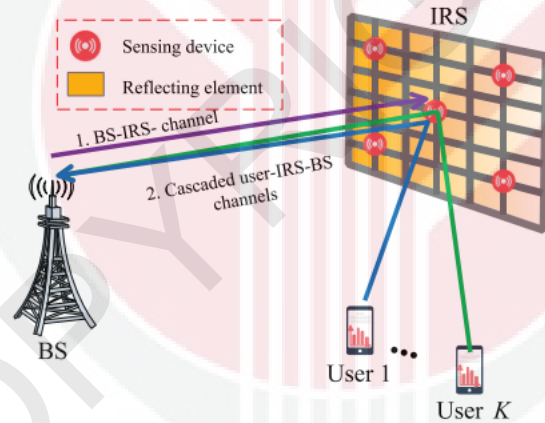


Figure 5.2: Hybrid/combined separate and cascaded channel estimation

iii. RIS in Higher Frequency bands (THz band)

To support extremely high data rates, reconfigurable intelligent surface (RIS)-assisted terahertz (THz) communication is considered to be a promising technology for future sixth-generation networks. However, due to the typical employment of hybrid beamforming architecture in THz systems, as well as the passive nature of RIS which

cannot process pilot signals, obtaining channel state information (CSI) is facing significant challenges.

iv. High Mobility Environments in RIS Systems

In current research, most RIS-assisted systems are optimized for static or low-mobility scenarios. High-mobility environments, such as vehicular networks or high-speed trains, present significant challenges in terms of maintaining stable channel state information (CSI) and effective beamforming, which RIS systems struggle to handle efficiently. Future research should focus on developing adaptive RIS architectures and channel estimation techniques that can dynamically adjust to high-mobility scenarios. This could involve designing real-time tracking algorithms and leveraging machine learning methods to predict CSI variations quickly, allowing for faster adjustment of RIS configurations. Additionally, integrating RIS with other 6G technologies, such as massive MIMO or AI-assisted beamforming, could mitigate the effects of fast-changing environments.

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APPENDICES

Information or data that is too detailed for the main body of the thesis may be included as appendices. Appendices include original data, summary, sideline or preliminary tests, tabulations, tables that contain data of lesser importance, very lengthy quotations, supporting decisions, forms and documents, computer printouts, detailed engineering drawings, and other pertinent documents. Appendix materials should be grouped by type, e.g., Appendix A: Questionnaire, Appendix B: Original data, Appendix C: Tables of results.

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LIST OF PUBLICATIONS

Hindawi Q2:

Hussein, W., Audah, K., Noordin, N. K., Kraiem, H., Flah, A., Fadlee, M., & Ismail, A. (2023). Least square estimation-based different fast fading channel models in MIMO-OFDM systems. *International Transactions on Electrical Energy Systems*, 2023.

Eos Assoc Q2:

Hussein, W., Noordin, Nor K., et al. "Cascaded and Separate Channel Estimation based on CNN for RIS-MIMO Systems." *Engineering, Technology & Applied Science Research* 14.3 (2024): 14768-14774.

Elsevier Q3:

Hussein, W., Audah, K., Noordin, N. K., Rasid, M. F. B., & Ismail, A. B. (2024). Super-Resolution Channel Estimation based Deep Learning in Reconfigurable Intelligent Surface Systems. *International Journal of Intelligent Systems and Applications in Engineering*, 12(15s), 659-669.

IET CommunicationQ2: Under Review

Wala'a Hussein, Nor Noordin, Mohd A.Rasid, et al. Deep Learning for Optimal Phase-Shift and Beamforming Based on Individual and Cascaded Channels Estimation in the RIS-MIMO System. *Authorea.com*, March 17, 2024.

