Linköping Studies in Science and Technology
Dissertation No. 2199

Signal Processing Aspects of Massive MIMO and IRS-Aided Communications

Özgecan Özdoğan

Linköping Studies in Science and Technology
Dissertations No. 2199

Signal Processing Aspects of Massive MIMO and IRS-Aided Communications

Özgecan Özdoğan

Division of Communication Systems
Department of Electrical Engineering (ISY)
Linköping University, 581 83 Linköping, Sweden
www.commsys.isy.liu.se

Linköping 2022

This is a Swedish Doctor of Philosophy thesis.
The Doctor of Philosophy degree comprises 240 ECTS credits of postgraduate studies

Cover: A close look at a cell-free massive MIMO system. The illustration is a heat map showing the signal power variations at different locations. The phase-shifted signals with equal powers are transmitted by four randomly located antennas to coherently combine the signals at a nearby user. The setup is inspired by Figure 1.12 of the book: Özlem Tugfe Demir, Emil Björnson and Luca Sanguinetti (2021), “Foundations of User-Centric Cell-Free Massive MIMO”, Foundations and Trends® in Signal Processing: Vol. 14, No. 3-4, pp 162–472.

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

<https://creativecommons.org/licenses/by-nc/4.0/>

Signal Processing Aspects of Massive MIMO and IRS-Aided Communications

© 2022 Özgecan Özdoğan, unless otherwise noted.

ISBN 978-91-7929-164-8 (print)

ISBN 978-91-7929-165-5 (PDF)

ISSN 0345-7524

Printed in Sweden by LiU-Tryck, Linköping 2022

Abstract

The data traffic in cellular networks has grown at an exponential pace for decades. This trend will most probably continue in the future, driven by new innovative applications. One of the key enablers of future cellular networks is the massive MIMO technology, and it has been started to be commercially deployed in many countries. A massive MIMO base station is equipped with a massive number (e.g., a hundred) of individually steerable antennas, which can be effectively used to serve tens of user equipments simultaneously on the same time-frequency resource. It can provide a notable enhancement of both spectral efficiency and energy efficiency in comparison with conventional MIMO.

In the prior literature, the achievable spectral efficiencies of massive MIMO systems with a practical number of antennas have been rigorously characterized and optimized when the channels are subject to either spatially uncorrelated or correlated Rayleigh fading. Typically, in massive MIMO research, i.i.d. Rayleigh fading or less frequently free-space line-of-sight (LoS) channel models are assumed since they simplify the analysis. Massive MIMO technology is able to support both rich scattering and LoS scenarios. Practical channels can consist of a combination of an LoS path and a correlated small-scale fading component caused by a finite number of scattering clusters that can be modeled by spatially correlated Rician fading. In Paper A, we consider a multi-cell scenario with spatially correlated Rician fading channels and derive closed-form achievable spectral efficiency expressions for different signal processing techniques.

Alternatively, a massive number of antennas can be spread over a large geographical area and this concept is called cell-free massive MIMO. In the canonical form of cell-free massive MIMO, the access points cooperate via a fronthaul network to spatially multiplex the users on the same time-frequency resource using network MIMO methods that only require locally obtained channel state information. Cell-free massive MIMO is a densely deployed system. Hence, the probability of having an LoS path between some access points and the users is quite high. In Paper B, we consider a practical scenario where the channels between the access points and the users are modeled with Rician fading.

The main theory for massive MIMO has been developed for uni-polarized single-antenna users. Wireless signals are polarized electromagnetic waves, and there exist two orthogonal polarization dimensions. The practical base stations and user equipments typically utilize dual-polarized antennas (i.e., two co-located antennas that respond to orthogonal polarizations) to squeeze in twice the number of antennas in the same physical enclosure, as well as capturing signal components from both dimensions. In Paper C, we study a single-cell massive MIMO system with dual-polarized antennas at both the base station and users. The channel modeling for dual-polarized channels is substantially more complicated than for conventional uni-polarized channels. A channel model that takes into account several practical aspects that arise when utilizing dual-polarization, such as channel cross-polar discrimination (XPD) and cross-polar receive and transmit correlations (XPC) is considered.

Another technology that has exciting prospects and is quickly gaining traction in wireless communications is intelligent reflecting surfaces (IRS). It is also known under the names reconfigurable intelligent surfaces and software-controlled metasurfaces. IRS is a thin two-dimensional metasurface that is used to aid communications. According to the application of interest, an IRS has the ability to control and transform electromagnetic waves that are impinging on it. In this thesis, we study different aspects of this technology such as pathloss modeling, channel estimation, and different technology use cases. In Paper D, we derive the pathloss model using physical optics techniques for an IRS that is configured to reflect an incoming wave from a far-field source towards a receiver in the far-field. In Paper E, we demonstrate how an IRS can be used to increase the rank of the channel matrix in LoS point-to-point MIMO communications by creating a controllable path that complements the uncontrollable paths. Bringing IRS technology into reality requires addressing many practical challenges. For instance, the proper configuration of an IRS critically depends on accurate channel state information. However, there are two main issues that complicate the channel acquisition with IRS. First, the IRS is not inherently equipped with transceiver chains. Therefore, it can not sense the pilot signals. Besides, introducing an IRS into an existing setup will increase the number of channel coefficients proportionally to the number of IRS elements. In Paper F, we present a deep learning-based approach for phase reconfiguration at an IRS in order to learn and make use of the local propagation environment.

Populärvetenskaplig sammanfattning

Datatrafiken i mobilnäten har växt i en exponentiell takt i decennier. Denna trend kommer med största sannolikhet att fortsätta i framtiden, pådriven av nya innovativa användarapplikationer. En av de viktigaste nya komponenterna i framtidens mobilnät är den massiva MIMO-tekniken, och den har börjat användas kommersiellt i många länder. En massiv-MIMO-basstation är box med ett stort antal (t.ex. hundra) individuellt styrbara antenner, som kan användas för att effektivt betjäna tiotals användarenheter på samma tids- och frekvensresurs. Denna teknik förväntas leda till en avsevärd förbättring av både spektraleffektivitet (bitar per sekund och Hertz) och energieffektivitet (bitar per Joule) i jämförelse med konventionell MIMO-teknik, för vilken endast ett fåtal användarenheter kan samsas om en tids- och frekvensresurs.

Spektraleffektiviteten för massiv-MIMO-system har karakteriserats och optimerats i tidigare arbeten under antaganden om att vågutbredningen ger upphov till trådlösa kanaler som kan modelleras statistiskt enligt antingen rumsligt okorrelerad eller korrelerad Rayleigh-fädning. Dessa modeller antar att det inte finns någon direkt siktlinje mellan sändaren och mottagaren, så att alla mottagna vågor har reflekterats på olika objekt i utbredningsmiljön. Några arbeten har även antagit deterministiska kanalmodeller där endast en direktvåg existerar, men mestadels bortsett från de reflekterade vågorna. Dessa tidigare arbeten slår fast att massiv-MIMO-tekniken fungerar väl under alla de studerade modellerna för vågutbredning. Praktiska kanaler kan dock bestå av en kombination av en direktvåg och korrelerad Rayleigh-fädning, som skapats av ett begränsat antal spridningskluster i distinkta vinkelriktningar. Detta har inte studerats i den tidigare litteraturen, men kan modelleras genom rumsligt korrelerad Rice-fädning. Artikel A behandlar denna modell och analyserar ett massiv MIMO-system med många basstationer och användare. Artikeln härleder nya matematiska uttryck på sluten form för spektraleffektiviteten, när olika signalbehandlingstekniker används för sändning och mottagning.

Ett alternativ till att bygga massiv-MIMO-basstationer med alla antenner i en box är att sprida ut antennerna över ett stort geografiskt område. Detta koncept

kallas cellfri massiv-MIMO eftersom ett sådant mobilnät inte längre skulle dela in täckningsområdet i distinkta celler, där varje cell är associerad med en specifik basstation, utan varje användarenhet skulle istället kopplas upp mot alla omgivande antenner. I den ursprungliga formen av cellfri massiv-MIMO samarbetar de utspridda antennerna via ett trådbundet fronthaul-nätverk för att kommunicera med användarna på samma tids- och frekvensresurs genom att skicka och motta signal från alla antennenpunkter. Signalerna processas för att ge upphov till en stark signal för den avsedda användaren och låg störning hos övriga användare. Det antas ofta att varje antenn endast använder kanalkännedom som den kan mäta upp lokalt och Rayleigh-fädningsmodeller utan direktvågor brukar användas för analys. Men eftersom grundtanken med cellfri massiv-MIMO är att antennerna är tätt utplacerade, så att de kommer nära användarna, är sannolikheten hög för att direktvågor existerar mellan varje antenn och dess mest närbelägna användare. Artikel B analyserar ett sådant praktiskt scenario där kanalerna mellan antennenpunkterna och användarenheterna kan modelleras med Rice-fädningsmodell.

Trådlösa signaler är polariserade elektromagnetiska vågor och det finns två ortogonala polarisationsdimensioner. Huvudteorin för massiv-MIMO-tekniken har utvecklats för användarenheter med endast en enkelpolariserad antenn. Dagens basstationer och användarenheter använder dock vanligtvis dubbelpolariserade antenner (dvs. två samplacade antenner som skapar och reagerar på signaler med ortogonala polarisationer). Fördelarna med detta är att dubbelt så många antenner får plats in samma box och att båda signaldimensionerna kan användas för kommunikation. Artikel C studerar en cell i ett massiv-MIMO-system med dubbelpolariserade antenner på både basstationen och användarenheterna. Kanalmodelleringen för dubbelpolariserade kanaler är avsevärt mer komplicerad än för konventionella enkelpolariserade kanaler. Artikeln expanderar huvudteorin för massiv-MIMO-tekniken för att ta hänsyn till de mest väsentliga praktiska aspekterna av att ha dubbel polarisation, såsom korspolär upplösning och korspolära mottagnings- och sändningskorrelationer.

Avhandlingen behandlar även ett nytt teknikkoncept som nyligen fått mycket uppmärksamhet: intelligenta reflekterande ytor. På engelska kallas de ofta intelligent reflecting surfaces (IRS) eller reconfigurable intelligent surfaces. En IRS är en tunn tvådimensionell yta som kan skapas av metamaterial och användas för att underlätta kommunikationen mellan andra punkter. Den karakteriserande egenskapen hos en IRS är att dess elektriska egenskaper kan förändras med tiden och därmed går det att styra hur elektromagnetiska vågor reflekteras av ytan. Ytan är indelad i många individuellt styrbara reflekterande element, liknande massiv-MIMO-tekniken, men skapar inte några egna signaler. I den här avhandlingen studerar vi olika aspekter av denna nya teknik, såsom modellering av sträckdämpning, skattning av kanalegenskaper och jämförelse av olika användningsfall. Artikel D härleder en sträckdämpningsmodell med hjälp av metoder från fysikalisk optik. Artikeln studerar ett fall där en IRS är

konfigurerad för att reflektera en inkommande våg från en fjärrfältskälla mot en mottagare i fjärrfältet. Artikel E demonstrerar hur en IRS kan användas för att öka den matematiska rangen hos den trådlösa kanalen, för att möjliggöra att flera olika signaler kan skickas från en sändare till en annan mottagare men ändå särskiljas i den rumsliga dimensionen. En signal kan skickas via direktvågen medan den styrbara utbredningsvägen via IRS:en kan konfigureras för att dess reflekterade signal ska upplevas så annorlunda som möjligt på mottagarsidan. Många praktiska utmaningar måste överbryggas för att den nya IRS-tekniken ska bli praktiskt användbar. En fundamental utmaning är att IRS-konfigurationen måste väljas baserat på kanalkännedom så att reflektionerna sker i rätt riktning. Det finns två huvudproblem som gör det svårt att mäta upp kanalen. För det första är IRS:en inte utrustad med några mottagare så den kan inte göra några egna mätningar. För det andra ökar antalet okända kanalkoefficienter som måste mätas proportionellt mot antalet IRS-element och en yta kan bestå av hundratals element. Många kända signaler måste därför skickas från sändaren till mottagaren för att mäta upp alla dessa koefficienter. Artikel F beskriver hur maskinlärning kan användas för att styra en IRS genom att kombinera mätningar med att lära sig den lokala trådlösa spridningsmiljön.

Özet

Hücresel ağlardaki veri trafiği, geçtiğimiz yıllarda katlanarak büyümüştür. Bu eğilim, büyük olasılıkla yenilikçi uygulamaların ortaya çıkmasıyla gelecekte de devam edecektir. Geleceğin hücresel ağlarının en önemli gerçekleştiricilerinden biri, birçok ülkede ticari olarak kullanılmaya başlanan massive MIMO teknolojisidir. Bir massive MIMO baz istasyonu, aynı zaman-frekans kaynağında aynı anda onlarca kullanıcı ekipmanına hizmet vermek için etkin bir şekilde kullanılabilen çok sayıda (örneğin yüz) ayrı ayrı yönlendirilebilir antenle donatılmıştır. Geleneksel MIMO ile karşılaştırıldığında hem spektral verimlilik hem de enerji verimliliğinde kayda değer bir iyileştirme sağlamaktadır.

Literatürde, pratik sayıda antene sahip massive MIMO sistemlerinin ulaşılabilir spektral verimlilikleri, kanalların uzamsal olarak ilişkisiz veya ilişkili Rayleigh sönmlemesine maruz kaldığı senaryolar için titizlikle karakterize edilmiş ve optimize edilmiştir. Tipik olarak, massive MIMO araştırmalarında, i.i.d. Rayleigh sönmmlü veya daha az sıklıkla açık görüş hattı (LoS) kanal modelleri, analizi basitleştirdiklerinden varsayılır. Massive MIMO teknolojisi, hem zengin saçılma hem de açık görüş hattı senaryolarını destekleyebilir. Pratik kanallar, bir açık görüş hattı ve uzamsal olarak ilişkili Rician sönmlemesi ile modellenebilen sonlu sayıda saçılma kümesinin neden olduğu ilişkili küçük ölçekli sönmleme bileşeninin bir kombinasyonundan oluşabilir. Makale A'da, uzamsal olarak ilişkili Rician sönmleme kanallarına sahip çok hücreli bir senaryoyu ele alıyoruz ve farklı sinyal işleme teknikleri için kapalı formda ulaşılabilir spektral verimlilik ifadeleri türetiyoruz.

Alternatif olarak, büyük bir coğrafi alana çok sayıda anten yayılabilir ve bu konsepte hücresiz massive MIMO denir. Hücresiz massive MIMO'nun kanonik biçiminde, erişim noktaları, yalnızca yerel olarak elde edilen kanal durumu bilgisini gerektiren ağ MIMO yöntemlerini kullanarak kullanıcıları aynı zaman-frekans kaynağında uzamsal olarak çoğullamak için bir ön taşıma ağı aracılığıyla işbirliği yapar. Hücresiz massive MIMO, yoğun bir şekilde konuşlandırılmış bir sistemdir. Bu nedenle, bazı erişim noktaları ile kullanıcılar arasında bir direkt görüş hattı olma olasılığı oldukça yüksektir. Makale B'de, erişim noktaları ve kullanıcılar arasındaki kanalların Rician sönmlemesi ile modellendiği pratik bir senaryo ele alıyoruz.

Massive MIMO için ana teori, tek kutuplu tek anten kullanıcıları için geliştirilmiştir. Kablosuz sinyaller polarize elektromanyetik dalgalar ve iki dikey polarizasyon boyutu vardır. Pratik baz istasyonları ve kullanıcı ekipmanları, tipik olarak, aynı fiziksel muhafaza içinde iki kat daha fazla anten sıkıştırmak ve ayrıca her iki boyuttan sinyal bileşenlerini yakalamak için çift kutuplu antenler (yani, dikey polarizasyonlara yanıt veren iki ortak konumlandırılmış anten) kullanır. Makale C’de, hem baz istasyonunda hem de kullanıcılarda çift kutuplu antenlere sahip tek hücreli bir massive MIMO sistemini inceliyoruz. Çift kutuplu kanallar için kanal modellemesi, geleneksel tek kutuplu kanallara göre önemli ölçüde daha karmaşıktır. Kanallar arası kutup ayrımı (XPD) ve kutuplar arası alma ve iletilme korelasyonları (XPC) gibi çift kutuplulaştırma kullanılırken ortaya çıkan birkaç pratik yönü hesaba katan bir kanal modeli göz önünde bulundurulur.

Heyecan verici olan ve kablosuz iletişimde hızla ivme kazanan bir diğer teknoloji, akıllı yansıtıcı yüzeylerdir (IRS). Ayrıca, yeniden yapılandırılabilir akıllı yüzeyler ve yazılım kontrollü metayüzeyler adları altında da bilinir. IRS, iletişime yardımcı olmak için kullanılan ince, iki boyutlu bir metayüzeydir. İlgilenilen uygulamaya göre, bir IRS, kendisine gelen elektromanyetik dalgaları kontrol etme ve dönüştürme yeteneğine sahiptir. Bu tezde, yol kaybı modellemesi, kanal tahmini ve farklı teknoloji kullanım durumları gibi bu teknolojinin farklı yönlerini inceliyoruz. Makale D’de, uzak alan kaynağından uzak alandaki bir alıcıya gelen bir dalgayı yansıtacak şekilde yapılandırılmış bir IRS için fiziksel optik teknikleri kullanarak yol kaybı modelini türetiyoruz. Makale E’de ise, kontrol edilemeyen yolları tamamlayan kontrol edilebilir bir yol oluşturarak açık görüş hattı noktadan noktaya MIMO iletişimlerinde kanal matrisinin rankını artırmak için bir IRS’nin nasıl kullanılabileceğini gösteriyoruz. IRS teknolojisini gerçeğe dönüştürmek, birçok pratik zorluğun aşılmasını gerektirir. Örneğin, bir IRS’nin doğru konfigürasyonu kritik olarak doğru kanal durumu bilgisine bağlıdır. Ancak, IRS ile kanal durumunun elde edilmesini zorlaştıran iki ana konu vardır. İlk olarak, IRS, doğası gereği alıcı-verici zincirleriyle donatılmamıştır. Bu nedenle pilot sinyalleri algılayamaz. Ayrıca, mevcut bir kurulumda bir IRS eklemek, IRS elemanlarının sayısı ile orantılı olarak kestirilmesi gereken kanal katsayılarının sayısını artıracaktır. Makale F’de, yerel yayılma ortamını öğrenmek ve kullanmak amacıyla IRSler için derin öğrenmeye dayalı bir faz yeniden yapılandırması yaklaşımı sunuyoruz.

Acknowledgments

First and foremost, I would like to express my innermost gratitude to my supervisor, Prof. Emil Björnson, for his excellent supervision. Thank you for your support, patience, encouragement, commitment, constructive feedback, inspiring ideas, and many more. I feel fortunate to have had the opportunity to learn from you. Likewise, I would like to thank my co-supervisor, Prof. Erik G. Larsson, for his expert advice, insightful comments, and suggestions.

To my colleagues at the Division of Communication Systems at Linköping University, I feel very lucky to have spent my Ph.D. period in an environment so full of expertise, collegiality, and warmth. I wish to express my warmest thanks to my friends who have made my time in Sweden more delightful with discussions on any real or fictitious problem one can think of. Without your supports and friendship, I can not even imagine how this journey could have been.

I want to thank my parents, İsmet and Hanife, and my sister Özden for their never-ending support. Also, I would like to thank my second family, my husband's family: Nurcan, Şener, Erdoğan, Emircan, Sedat, and Mukaddes, for their support, making tough times a lot easier. Thank you for being a source of laughter and stress relief.

Vedat, thank you for standing by my side through highs and lows. It has been precious to share my life with you. Now, I am excited for the post-PhD chapter of our lives, Dr. Vedat!

Özgecan Özdoğan
Linköping, December 2021

Contents

1	Introduction	1
1.1	Background and Motivation	1
1.2	Contributions of the Thesis	6
1.2.1	Papers Included in the Thesis	7
1.2.2	Papers Not Included in the Thesis	10
2	Channel Models for Massive MIMO	13
2.1	Channel Fading	13
2.2	Line-of-Sight Channels	15
2.3	Spatially Uncorrelated Rayleigh Fading	18
2.4	Spatially Correlated Rayleigh Fading	21
2.5	Spatially Correlated Rician Fading	26
2.6	Impact of LoS path and Spatial Correlation in Massive MIMO . . .	28
3	Basics of Massive MIMO	33
3.1	Duplexing Protocol	33
3.2	Channel Estimation	35
3.3	Uplink Data Transmission	36
3.4	Downlink Data Transmission	38
4	Dual-Polarized Channels	41
4.1	Antenna Polarization	43
4.2	Channel Depolarization	47
5	Intelligent Reflecting Surfaces	51
5.1	What is an IRS?	51
5.2	Basics of System Modeling with IRS	52
5.3	Prospective Use Cases	54

6	Deep Learning for Wireless Communications	57
6.1	Preliminaries of Feedforward Neural Networks	58
6.2	Applications to Wireless Communications	60
	Bibliography	61
	Included Papers	73
A	Massive MIMO with Spatially Correlated Rician Fading Channels	75
1	Introduction	77
1.1	Main Contributions	78
2	Channel and System Model	79
3	Channel Estimation	80
3.1	MMSE Channel Estimator	81
3.2	Element-wise MMSE Channel Estimator	82
3.3	LS Channel Estimator	82
4	Uplink Spectral efficiency with MR combining	83
4.1	Uplink Spectral Efficiency with MMSE estimator	84
4.2	Uplink Spectral Efficiency with EW-MMSE Estimator	85
4.3	Uplink Spectral Efficiency with LS Estimator	86
4.4	Uplink Spectral Efficiency with Mean Only Estimator	87
5	Downlink Spectral Efficiency with MR Precoding	88
5.1	Downlink Spectral Efficiency with MMSE Estimator	88
5.2	Downlink Spectral Efficiency with EW-MMSE Estimator	90
5.3	Downlink Spectral Efficiency with LS Estimator	90
5.4	Downlink Spectral Efficiency with Mean Only Estimator	91
6	Asymptotic Analysis	91
6.1	Asymptotic Analysis of Spectral Efficiency with MMSE Estimator	92
6.2	Asymptotic Analysis of Spectral Efficiency with EW-MMSE Estimator	93
6.3	Asymptotic Analysis of Spectral Efficiency with LS Estimator	94
6.4	Asymptotic Analysis of Spectral Efficiency with Mean Only Estimator	94
6.5	Discussion on the Asymptotic Behaviors of Rician Fading Channels	95
7	Numerical Results	95
8	Conclusion	101
9	Appendix	102
9.1	Useful results	102

9.2	Proof of Lemma 4 and Lemma 5	103
9.3	Proof of Lemma 3	104
9.4	Proof of Theorem 1	104
9.5	Proof of Theorem 2	106
9.6	Proof of Theorem 3	106
9.7	Proof of Theorem 7 and Theorem 8	108
9.8	Proof of Theorem 9 and Theorem 10	108
9.9	Proof of Theorem 11	109
	References	110
B	Cell-Free Massive MIMO with Rician Fading and Phase Shifts	115
1	Introduction	117
2	System Model	119
3	Uplink Channel Estimation	120
3.1	Phase-aware MMSE Channel Estimator	121
3.2	LMMSE Channel Estimator	122
3.3	LS Channel Estimator with No Prior Information	123
4	Uplink Data Transmission	124
4.1	Uplink Spectral Efficiency with the Phase-aware MMSE Estimator	127
4.2	Uplink Spectral Efficiency with the LMMSE Estimator	127
4.3	Uplink Spectral Efficiency with the LS Estimator	128
5	Coherent Downlink Transmission	129
5.1	Coherent Downlink Spectral Efficiency with the Phase-aware MMSE Estimator	130
5.2	Coherent Downlink Spectral Efficiency with the LMMSE Estimator	131
5.3	Coherent Downlink Spectral Efficiency with the LS Estimator	132
6	Non-coherent Downlink Transmission	132
6.1	Non-coherent Downlink Spectral Efficiency with the Phase-aware MMSE Estimator	133
6.2	Non-Coherent Downlink Spectral Efficiency with the LMMSE and LS Estimator	134
7	Numerical Results	135
8	Conclusion	142
9	Appendix	143
9.1	Derivation of the LMMSE Estimator	143
9.2	Derivation of the LS Estimator	143
9.3	Proof of UL and DL SE with MMSE estimator	144
9.4	Proof of UL and DL SE with LMMSE Estimator	148

9.5	Proof of UL and DL SE with the LS Estimator	150
9.6	Proof of DL SE with Non-coherent Transmission	152
	References	153
C	Massive MIMO with Dual-Polarized Antennas	157
1	Introduction	159
2	System model with dual-polarized antennas	161
3	Channel Estimation	166
4	Uplink Transmission	167
4.1	Uplink Linear Detection	168
4.2	Uplink MMSE-SIC detection	170
5	Downlink Transmission	171
5.1	Downlink Linear Processing	172
5.2	Downlink MMSE-SIC Processing	172
6	Power Control	174
6.1	Uplink Power Control	174
6.2	Downlink Power Control	175
7	Numerical Results	176
8	Conclusions	184
9	Appendix	185
9.1	Proof of Lemma 3	185
9.2	Proof of Lemma 6	187
	References	189
D	Intelligent Reflecting Surfaces: Physics, Propagation, and Pathloss Modeling	193
1	Introduction	195
2	Preliminaries: Passive Metallic Surface	196
2.1	Beamwidth of the Scattered Wave	198
2.2	Multiple Adjacent Metallic Surfaces	200
3	System Model for Intelligent Metasurfaces	200
3.1	Propagation and Pathloss Model	202
3.2	Interpreting an IRS as an Array of Diffuse Scatterers	204
3.3	System Model for IRS-Supported Communications	205
4	Summary and Relation to Prior Work	206
	References	206
E	Using Intelligent Reflecting Surfaces for Rank Improvement in MIMO Communications	209
1	Introduction	211
1.1	Relation to Prior Work	212

2	System Model	212
3	Downlink Transmission	214
3.1	Case 1: Direct Transmission	214
3.2	Case 2: IRS-aided transmission	215
3.3	Deployment Analysis	217
4	Numerical Results	218
5	Conclusion	222
	References	222

F	Deep Learning-based Phase Reconfiguration for Intelligent Reflecting Surfaces	225
1	Introduction	227
2	System Model with IRS supported transmission	228
2.1	Channel Estimation	229
2.2	IRS Phase Reconfiguration and Downlink Spectral Efficiency	231
3	Deep Learning-based Phase Configuration	232
3.1	Deep Learning Method 1	233
3.2	Deep Learning Method 2	234
4	Numerical Results	234
5	Conclusions	237
	References	238

Chapter 1

Introduction

1.1 Background and Motivation

The initial understanding of radio wave propagation and the concept of wireless communication date back to the 19th century. In 1895, the entrepreneur Guglielmo Marconi successfully transmitted and received a coded message at a distance of 3.2 kilometers near his home in Bologna, Italy. Since then, the number of voice and data connections has doubled every 30 months [1]. Today, wireless connectivity has fundamentally changed the way we communicate and it is an integral part of our lives.

In its most elementary form, wireless communication is performed between a single transmitting antenna at the source and a single receiving antenna at the destination. This single-input single-output (SISO) wireless technology has been in use since the invention of wireless communication. However, the wireless propagation environments may pose severe challenges (see Section 2.1 for a more detailed explanation) and SISO is not robust to these challenging propagation conditions. To combat the channel impediments and receive a strong signal with SISO, a straightforward approach may be increasing the transmit power. However, this technique has two main drawbacks. First, the demanded mobile data volumes unprecedentedly inflate and it is not feasible to increase the transmit power boundlessly. Second, the number of connected devices unceasingly increases. Their signals would interfere with each other and the network may be easily pushed to an interference-limited regime. Instead of increasing the transmit power, an alternative approach is to increase the number of antennas at the transmitter or the receiver, or at both ends. By doing so, more power can be collected from the electromagnetic waves.

Remarkably in the 1920s, radio engineers H. H. Beverage and H. O. Peterson noticed that radio broadcast signals at two stations located about a half-mile apart had very different received signal strengths due to different levels of fading. To overcome

this issue, they developed a multiple antenna system with two receiver antenna for each radio station. Further, their experimental observations indicated that these antennas needed to be separated by at least a wavelength for reliable operation [2].

MIMO technology has several prominent advantages over SISO in terms of array, diversity and multiplexing gains. Array gain means a power gain of the transmitted signal achieved using by multiple antennas at the transmitter and/or receiver compared with that of SISO systems. The usage of multiple antennas at the transmitter enables directional beamforming that can be used to point the signal towards the user. Likewise, using multiple antennas at the receiver side provides a power gain since the receiver can collect more power from the transmitted signal. In addition, these antennas can provide a spatial diversity gain since they receive different copies of the same signal, which may unlikely to all be nearly zero simultaneously. The diversity can dramatically improve the performance when communicating under challenging channel conditions and provide more reliable wireless links. Moreover, having multiple antennas at the both ends provides an additional spatial dimension for communication and yields a multiplexing gain. The transmitter can separate the received signals in the spatial domain such that multiple parallel data streams can be supported on the same time and frequency resource. Spatial multiplexing of several data streams concurrently leads to an increase in the rate that is proportional to the number of data streams under ideal signal conditions.

Figure 1: A basic illustration of a cellular network with massive MIMO base stations.

As mentioned above, we observe an unceasingly increasing data traffic. This trend is expected to continue in the near future [3]. Massive MIMO technology is one of the key enablers of 5G wireless networks, by virtue of beamforming and

spatial multiplexing. A massive MIMO base station is equipped with a massive number (e.g., a hundred) of individually steerable antennas, which can be effectively used to serve tens of user equipments simultaneously on the same time-frequency resource. Figure 1 depicts an illustration of a cellular massive MIMO network. It is relatively more convenient to deploy multiple antennas at the base station than at the users since the user equipments are generally compact, commercial and powered by small batteries and therefore less reliable products. Massive MIMO can provide higher data rates without the need for more bandwidth or dense deployment of base stations. It is an efficient way to achieve high spectral efficiency (bit/s/Hz) per cell and per user. A massive MIMO base station can serve more users compared to a conventional MIMO base station and this results in a higher spectral efficiency per cell. Additionally, increased array gain and beamforming directivity reduce the inter-user interference that brings higher spectral efficiency per user.

After the seminal paper [4] providing the initial framework of massive MIMO with infinitely many antennas, the achievable spectral efficiencies of massive MIMO systems with practical number of antennas have been rigorously characterized and optimized by either spatially uncorrelated [5] or correlated Rayleigh fading [6, 7]. Further, massive MIMO communication with free-space line-of-sight (LoS) propagation, meaning that the environment is scatterer free and there is a direct path between the transmitter and the receiver, is treated in [8]. In massive MIMO research, i.i.d. Rayleigh fading or less commonly free-space LoS channel models are quite popular since they simplify the analysis. Massive MIMO technology is able to support both rich scattering and LoS scenarios. However, practical channels can consist of a combination of an LoS path (often called a specular path) and a correlated small-scale fading component caused by a finite number of scattering clusters that can be modeled by spatially correlated Rician fading (see Section 2.5 for a more detailed explanation). These channel models are discussed in detail in the later sections. The performance of massive MIMO with Rician fading channels is much less analyzed than the others. Paper A considers a multi-cell scenario with spatially correlated Rician fading channels and derives closed-form achievable spectral efficiency expressions for different signal processing techniques.

A radically different way of deploying a massive number of antennas is spreading them over a large geographical area [9, 10]. This concept is called cell-free massive MIMO and has attracted lots of interest, see for example [11–15]. Figure 2 shows an illustration of a cell-free massive MIMO network. The idea of distributed antennas has been around for many years and various other names have been given to it in the past, such as network MIMO [16, 17] or cooperative multipoint (CoMP) [18, 19]. Different from the network MIMO or CoMP, larger number of antennas are employed in cell-free massive MIMO and the benefits of massive MIMO are exploited. The main advantages of distributing the antennas are spatial diversity, increased

Figure 2: A cell-free massive MIMO network.

coverage and possibility of providing uniform service. In [20], cell-free massive MIMO is described as an intersection of three technological concepts: physical layer from cellular massive MIMO, the idea of joint transmission of distributed antennas from the CoMP literature, and the deployment regime of ultra-dense networks. Therefore, the goal is to combine the best aspect of these three technologies. In the canonical form of a cell-free system, the access points cooperate via a fronthaul network to spatially multiplex the users on the same time-frequency resource using network MIMO methods that only require locally obtained channel state information [14, 21].

Cell-free massive MIMO is a densely deployed system. Hence, the probability of having an LoS path between some access points and the users is quite high. Despite that, in early works, Rayleigh fading is assumed [12, 13]. In Paper B, we consider a practical scenario where the channels between the access points and the users are modeled with Rician fading. Moreover, taking into account mobility of the users and hardware impairments, the LoS phase is modeled as a uniformly distributed random variable. Considering the availability of prior information at the access points, the phase-aware minimum mean square error (MMSE), non-aware linear MMSE (LMMSE), and least-square (LS) estimators are derived. In the uplink, a two-layer decoding method is investigated in order to mitigate both coherent and non-coherent interference. Closed-form uplink spectral efficiency expressions with

phase-aware MMSE, LMMSE, and LS estimators are derived for maximum-ratio (MR) combining in the first layer and optimal large-scale fading decoding (LSFD) in the second layer. In the downlink, two different transmission modes are studied: coherent and non-coherent. Closed-form downlink spectral efficiency expressions for both transmission modes with MR precoding are derived for the three estimators.

The main theory for massive MIMO has been developed for uni-polarized single-antenna users. Wireless signals are polarized electromagnetic waves, and there exist two orthogonal polarization dimensions. The practical base stations and user equipments typically utilize dual-polarized antennas (i.e., two co-located antennas that respond to orthogonal polarizations) to squeeze in twice the number of antennas in the same physical enclosure, as well as capturing signal components from both dimensions. In Paper C, we study a single-cell massive MIMO system with dual-polarized antennas at both the base station and users. The channel modeling for dual-polarized channels is substantially more complicated than for conventional uni-polarized channels. A channel model that takes into account several practical aspects that arise when utilizing dual-polarization, such as channel cross-polar discrimination (XPD) and cross-polar receive and transmit correlations (XPC) is considered.

Figure 3: An illustration of an IRS-assisted communication system.

Another technology that has exciting prospects and is quickly gaining traction in wireless communications is intelligent reflecting surfaces (IRS). It is also known under the names reconfigurable intelligent surfaces and software-controlled metasurfaces. IRS is a thin two-dimensional metasurface that is used to aid communications. Figure 3 illustrates an IRS-assisted communication system. According to the application of interest, an IRS has the ability to control and transform electromagnetic waves

that are impinging on it. In this thesis, we study different aspects of this technology such as pathloss modeling, channel estimation, and different technology use cases. In Paper D, we derive the pathloss model using physical optics techniques for an IRS that is configured to reflect an incoming wave from a far-field source towards a receiver in the far-field. In Paper E, we demonstrate how an IRS can be used to increase the rank of the channel matrix in LoS point-to-point MIMO communications by creating a controllable path that complements the uncontrollable paths. Bringing IRS technology into reality requires addressing many practical challenges. For instance, the proper configuration of an IRS critically depends on accurate channel state information. However, there are two main issues that complicate the channel acquisition with IRS. First, the IRS is not inherently equipped with transceiver chains. Therefore, it can not sense the pilot signals. Besides, introducing an IRS into an existing setup will increase the number of channel coefficients proportionally to the number of IRS elements. In Paper F, we present a deep learning-based approach for phase reconfiguration at an IRS in order to learn and make use of the local propagation environment.

1.2 Contributions of the Thesis

This thesis considers signal processing aspects of massive MIMO and IRS-aided communications. Paper A and Paper B focus on analysis of cellular and cell-free massive MIMO with Rician fading. The main theory of massive MIMO is developed for uni-polarized channels. Paper C studies dual-polarized channels in a single-cell massive MIMO system. Finally, different aspects of IRS-assisted communications are studied in Paper D, Paper E and Paper F. In Paper D, we derive a far-field pathloss model. Paper E studies point-to-point LoS channels and introduces an additional path to increase channel rank via an IRS. In Paper F, we propose a deep learning based IRS configuration method using the received pilot signals.

The main ideas and topics researched in this dissertation have emerged from the combined effort of the first author, supervisor, and co-supervisor. The analysis and writing of the papers presented in this dissertation have all been conducted by the first author with careful guidance and advice from her supervisor and co-supervisors. The first author would like to acknowledge the contributions provided by the supervisor, co-supervisors, and other authors through careful revision of manuscripts and analysis, as well as sharing their expert advice on review processes, research directions, and general knowledge.

In this section, we provide the publication information for the papers that are included in this thesis and further list other publications that are not included.

1.2.1 Papers Included in the Thesis

Paper A: Massive MIMO with Spatially Correlated Rician Fading Channels

Authored by: Özgecan Özdoğan, Emil Björnson, and Erik G. Larsson

Published in: IEEE Transactions on Communications, vol. 67, no. 5, pp. 3234-3250, May 2019

Abstract: This paper considers multi-cell massive multiple-input multiple-output systems, where the channels are spatially correlated Rician fading. The channel model is composed of a deterministic line-of-sight path and a stochastic non-line-of-sight component describing a practical spatially correlated multipath environment. We derive the statistical properties of the minimum mean squared error (MMSE), element-wise MMSE, and least-square channel estimates for this model. Using these estimates for maximum ratio combining and precoding, rigorous closed-form uplink (UL) and downlink (DL) achievable spectral efficiency (SE) expressions are derived and analyzed. The asymptotic SE behavior, when using the different channel estimators, are also analyzed. The numerical results show that the SE is higher when using the MMSE estimator than that of the other estimators, and the performance gap increases with the number of antennas.

Paper B: Performance of Cell-Free Massive MIMO With Rician Fading and Phase Shifts

Authored by: Özgecan Özdoğan, Emil Björnson, and Jiayi Zhang

Published in: IEEE Transactions on Wireless Communications, vol. 18, no. 11, pp. 5299-5315, November 2019

Abstract: In this paper, we study the uplink (UL) and downlink (DL) spectral efficiency (SE) of a cell-free massive multiple-input-multiple-output (MIMO) system over Rician fading channels. The phase of the line-of-sight (LoS) path is modeled as a uniformly distributed random variable to take the phase-shifts due to mobility and phase noise into account. Considering the availability of prior information at the access points (APs), the phase-aware minimum mean square error (MMSE), non-aware linear MMSE (LMMSE), and least-square (LS) estimators are derived. The MMSE estimator requires perfectly estimated phase knowledge whereas the LMMSE and LS are derived without it. In the UL, a two-layer decoding method is investigated in order to mitigate both coherent and non-coherent interference. Closed-form UL SE expressions with phase-aware MMSE, LMMSE, and LS estimators are derived for maximum-ratio (MR) combining in the first layer and optimal large-scale fading decoding (LSFD) in the second layer. In the DL, two different transmission modes are studied: coherent and non-coherent. Closed-form DL SE expressions for

both transmission modes with MR precoding are derived for the three estimators. Numerical results show that the LSFD improves the UL SE performance and coherent transmission mode performs much better than non-coherent transmission in the DL. Besides, the performance loss due to the lack of phase information depends on the pilot length and it is small when the pilot contamination is low.

Paper C: Massive MIMO with Dual-Polarized Antennas

Authored by: Özgecan Özdoğan, Emil Björnson

Submitted to: IEEE Transactions on Wireless Communications

Abstract: This paper considers a single-cell massive MIMO (multiple-input multiple-output) system with dual-polarized antennas at both the base station and users. We study a channel model that takes into account several practical aspects that arise when utilizing dual-polarization, such as channel cross-polar discrimination (XPD) and cross-polar correlations (XPC) at the transmitter and receiver. We analyze uplink and downlink achievable spectral efficiencies (SE) with and without successive interference cancellation (SIC) for the linear minimum mean squared error (MMSE), zero-forcing (ZF) and maximum ratio (MR) combining/precoding schemes. In addition, we derive the statistical properties of the MMSE channel estimator for the dual-polarized channel model. These estimates are used to implement different precoding and combining schemes when the uplink and downlink SE expressions are calculated for the case. Closed-form uplink and downlink SE expressions for MR combining/precoding are derived. Based on these results, we also provide power control algorithms to maximize the uplink and downlink sum SEs. Moreover, we compare the SEs achieved in dual-polarized and uni-polarized setups numerically and evaluate the impact of XPD and XPC.

Paper D: Intelligent Reflecting Surfaces: Physics, Propagation, and Pathloss Modeling

Authored by: Özgecan Özdoğan, Emil Björnson, and Erik G. Larsson

Published in: IEEE Wireless Communications Letters, vol. 9, no. 5, pp. 581-585, May 2020

Abstract: Intelligent reflecting surfaces can improve the communication between a source and a destination. The surface contains metamaterial that is configured to “reflect” the incident wave from the source towards the destination. Two incompatible pathloss models have been used in prior work. In this letter, we derive the far-field pathloss using physical optics techniques and explain why the surface consists of many elements that individually act as diffuse scatterers but can jointly beamform the signal in a desired direction with a certain beamwidth. We disprove one of the previously conjectured pathloss models.

Paper E: Using Intelligent Reflecting Surfaces for Rank Improvement in MIMO Communications

Authored by: Özgecan Özdoğan, Emil Björnson, and Erik G. Larsson

Published in: IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2020

Abstract: An intelligent reflecting surface (IRS), consisting of reconfigurable meta-materials, can be used to partially control the radio environment and thereby bring new features to wireless communications. Previous works on IRS have particularly studied the range extension use case and under what circumstances the new technology can beat relays. In this paper, we study another use case that might have a larger impact on the channel capacity: rank improvement. One of the classical bottlenecks of point-to-point MIMO communications is that the capacity gains provided by spatial multiplexing are only large at high SNR, and high SNR channels are mainly appearing in line-of-sight (LoS) scenarios where the channel matrix has low rank and therefore does not support spatial multiplexing. We demonstrate how an IRS can be used and optimized in such scenarios to increase the rank of the channel matrix, leading to substantial capacity gains.

Paper F: Deep Learning-based Phase Reconfiguration for Intelligent Reflecting Surfaces

Authored by: Özgecan Özdoğan, Emil Björnson

Published in: 54th Asilomar Conference on Signals, Systems, and Computers, November 2020

Abstract: Intelligent reflecting surfaces (IRSs), consisting of reconfigurable meta-materials, have recently attracted attention as a promising cost-effective technology that can bring new features to wireless communications. These surfaces can be used to partially control the propagation environment and can potentially provide a power gain that is proportional to the square of the number of IRS elements when configured in a proper way. However, the configuration of the local phase matrix at the IRSs can be quite a challenging task since they are purposely designed to not have any active components, therefore, they are not able to process any pilot signal. In addition, a large number of elements at the IRS may create a huge training overhead. In this paper, we present a deep learning (DL) approach for phase reconfiguration at an IRS in order to learn and make use of the local propagation environment. The proposed method uses the received pilot signals reflected through the IRS to train the deep feedforward network. The performance of the proposed approach is evaluated and the numerical results are presented.

1.2.2 Papers Not Included in the Thesis

The following publications contain the papers contributed by the author during her doctoral studies. They are not included in the thesis since they were either earlier versions of the journals, or the author did not make the most significant contribution.

Uplink Spectral Efficiency of Massive MIMO with Spatially Correlated Rician Fading

Authored by: Özgecan Özdoğan, Emil Björnson, and Erik G. Larsson

Published in: IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), June 2018

This paper contains preliminary results of Paper A.

Abstract: This paper considers the uplink (UL) of a multicell Massive MIMO (multiple-input multiple-output) system with spatially correlated Rician fading channels. The channel model is composed of a deterministic line-of-sight (LoS) path and a stochastic non-line-of-sight (NLoS) component describing a spatially correlated multipath environment. We derive the statistical properties of the minimum mean squared error (MMSE) and least-square (LS) channel estimates for this model. Using these estimates for maximum ratio (MR) combining, rigorous closed-form UL spectral efficiency (SE) expressions are derived. Numerical results show that the SE is higher when using the MMSE estimator than the LS estimator, and the performance gap increases with the number of antennas. Moreover, Rician fading provides higher achievable SEs than Rayleigh fading since the LoS path improves the sum SE.

Cell-Free Massive MIMO with Rician Fading: Estimation Schemes and Spectral Efficiency

Authored by: Özgecan Özdoğan, Emil Björnson, and Jiayi Zhang

Published in: 52nd Asilomar Conference on Signals, Systems, and Computers, November 2018

Abstract: As the cell sizes in cellular networks shrink, the inter-cell interference becomes more of an issue. Instead of operating each cell autonomously, we can connect all the access points (APs) together to form a cell-free massive MIMO (multiple-input multiple-output) system that can alleviate interference by spatial processing. Previous studies have focused on Rayleigh fading channels, but in densely deployed systems, it is likely that some of the users will have line-of-sight (LoS) propagation to some of the APs. In this paper, we model this by arbitrarily distributed Rician fading channels. Two types of channel estimators are considered: a classical least-square (LS) estimator and a Bayesian minimum mean square error (MMSE) estimator. We derive closed-form spectral efficiency (SE) expressions for the uplink

(UL) and downlink (DL) when using each of these estimators for maximum ratio (MR) processing. The performance difference is evaluated numerically to figure out under which conditions it is beneficial to know the channel statistics when estimating a channel.

Downlink Performance of Cell-Free Massive MIMO with Rician Fading and Phase Shifts

Authored by: Özgecan Özdoğan, Emil Björnson, and Jiayi Zhang

Published in: IEEE 20th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), July 2019

This paper contains preliminary results of Paper B.

Abstract: In this paper, we study the downlink (DL) spectral efficiency (SE) of a cell-free massive multiple-input-multiple-output (MIMO) system with Rician fading channels. The phase of the line-of-sight (LoS) path is modeled as a uniformly distributed random variable to take the phase-shifts due to mobility and phase noise into account. Considering the availability of prior information at the access points (APs), the phase-aware minimum mean square error (MMSE) and non-aware linear MMSE (LMMSE) estimators are derived. The MMSE estimator requires perfectly estimated phase knowledge whereas the LMMSE is derived without it. Besides, two different transmission modes are studied: coherent and non-coherent. Closed-form DL SE expressions for both coherent and non-coherent transmission with maximum-ratio (MR) precoding are derived for the two estimators. Numerical results show that the performance loss due to the lack of phase information is small and coherent transmission mode performs much better than non-coherent transmission.

Intelligent Reflecting Surface vs. Decode-and-Forward: How Large Surfaces Are Needed to Beat Relaying?

Authored by: Emil Björnson, Özgecan Özdoğan, and Erik G. Larsson

Published in: IEEE Wireless Communications Letters, vol. 9, no. 2, pp. 244-248, February 2020

Abstract: The rate and energy efficiency of wireless channels can be improved by deploying software-controlled metasurfaces to reflect signals from the source to destination, especially when the direct path is weak. While previous works mainly optimized the reflections, this letter compares the new technology with classic decode-and-forward (DF) relaying. The main observation is that very high rates and/or large metasurfaces are needed to outperform DF relaying, both in terms of minimizing the total transmit power and maximizing the energy efficiency, which also includes the dissipation in the transceiver hardware.

Reconfigurable Intelligent Surfaces: Three Myths and Two Critical Questions

Authored by: Emil Björnson, Özgecan Özdogan, and Erik G. Larsson

Published in: IEEE Communications Magazine, vol. 58, no. 12, pp. 90-96,
December 2020

Abstract: The search for physical layer technologies that can play a key role in beyond 5G systems has started. One option is reconfigurable intelligent surfaces (RISs), which can collect wireless signals from a transmitter and passively beamform them toward the receiver. The technology has exciting prospects and is quickly gaining traction in the communication community, but in the current hype we have witnessed how several myths and overstatements are spreading in the literature. In this article, we take a neutral look at the RIS technology. We first review the fundamentals and then explain specific features that can be easily misinterpreted. In particular, we debunk three myths: 1) current network technology can only control the transmitter and receiver, not the environment in between; 2) a better asymptotic array gain is achieved than with conventional beamforming; 3) the path loss is the same as with anomalous mirrors. To inspire further research, we conclude by identifying two critical questions that must be answered for RIS to become a successful technology: 1) What is a convincing use case for RIS?; 2) How can we estimate channels and control an RIS in real time?

Downlink Spectral Efficiency of Massive MIMO with Dual-Polarized Antennas

Authored by: Özgecan Özdogan, Emil Björnson

Published in: 25th International ITG Workshop on Smart Antennas (WSA),
November 2021

This paper contains preliminary results of Paper C.

Abstract: This paper considers the downlink of a single-cell massive MIMO (multiple-input multiple-output) system with dual-polarized antennas at both the base station and users. We consider a channel model that takes into account several practical aspects that arise when utilizing dual polarization, such as channel cross-polar discrimination (XPD) and cross-polar receive and transmit correlations (XPC). We derive the statistical properties of the minimum mean squared error (MMSE) channel estimator for this model. Using these estimates for maximum ratio precoding, a rigorous closed-form downlink spectral efficiency (SE) expression is derived. We compare the SEs achieved in dualpolarized and uni-polarized setups numerically and evaluate the impact of XPD on the downlink SE.

Chapter 2

Channel Models for Massive MIMO

In this section, we discuss some common channel models for massive MIMO in further detail. In particular, we focus on the effects of spatial correlation and of the LoS path.

2.1 Channel Fading

In wireless communications, electromagnetic waves are designed to carry information from a source to a destination. The electromagnetic theory of light was formulated by James Clerk Maxwell in 1864. In his pioneering work, he predicted the existence of radio waves. Later on, Heinrich Rudolf Hertz proved the existence of these radio waves by conducting a series of experiments.

One of the main challenges in wireless communications is that the emitted waves often do not reach the receiving antenna directly due to the obstacles in the propagation environment. The received wave is a superposition of waves coming from many directions due to reflection, scattering, and diffraction caused by buildings, trees, cars, and other objects. Reflection occurs when the wave bounces off a smooth object that is exceedingly large compared to the wavelength. Then, each incoming wave is mapped onto a single beam. Scattering happens when the wave propagates through a medium that contains objects whose dimensions are smaller or comparable to the wavelength. Thus, each incoming wave is mapped onto many scattered ones. The radio waves can also be bent around sharp edges, such as rooftops, and this phenomenon is referred to as diffraction [22].

Ideally, the electromagnetic wave propagation can be exactly modeled by solving Maxwell's equations. In a fixed environment, this requires the calculation of radar

cross sections of all surrounding objects. In a mobile environment, the obstacles change with time and their effects should also be taken into account. In general, these calculations are not computationally feasible and many required parameters are rarely available. Therefore, in wireless communications, Maxwell's equations are not used to model the propagation of transmitted signals. Instead, the waves are approximated as ray-of-lights and ray-tracing methods are employed. Based on this approximation, the ray propagation in different environments for various frequency bands are constructed by computer simulations. Some ray tracing methods attempt to reproduce the propagation mechanisms (reflection, scattering, and diffraction) in an actual physical location, for example see [23, 24]. Other techniques create virtual scenarios for performance evaluation [25]. In realistic and complicated environments, the ray-based approaches often fail to model the propagation accurately or they can be computationally very demanding. In those cases, empirical measurements and models can be utilized.

When a wave reaches the receiver by two or more paths, this phenomenon is called the multipath effect. The deterministic ray-tracing methods are useful when the number of paths is small. In general, the time-varying and complex nature of the radio channels prohibit to obtain an accurate model using deterministic methods. In practice, the number of paths is large and statistical models are utilized to characterize the constructive and destructive addition of different multipath components. The time-varying nature of the propagation channels stems from the movement of the transmitter and the receiver or the objects in the environment that changes the characteristics of the multipaths. Therefore, amplitudes and time delays of the transmitted waves unpredictably fluctuate over time.

The variations in the received power that is described above is called fading. The propagation effects that cause fading are classified as large-scale and small-scale effects. Path loss due to dissipation of the radiated power over the distance and shadow fading caused by obstacles that absorb power are referred to as large-scale fading effects. The fluctuations due to multipaths create the small-scale fading effects. These variations are referred to as small-scale fading because they occur when the user moves over short distances, at the order of the signal wavelength, whereas large-scale fading effects occur when the user moves over larger distances.

A distinct multipath component of the channel can be in the form of a single scatterer or a cluster of scatterers. In a multipath channel, when a single pulse is emitted from the transmitter, it is reflected by these scatterers. Due to this dispersive nature of the wireless channels, a pulse train is received at the destination with different time delays. The time delay between the first received and the last received pulses is referred to as the time delay spread of the channel. When the delay spread is large relative to the inverse of the signal bandwidth, the signal is scattered from different multipath components and interfere with subsequently transmitted pulses.

This effect is called intersymbol interference and may lead a substantial signal distortion. These channels are referred to as wideband channels. If the delay spread is smaller than the inverse of the signal bandwidth then the received signal is less distorted and these channels are called narrowband channels.

A classical solution to the intersymbol interference problem is to divide the bandwidth into many subcarriers each having a sufficiently narrow bandwidth. The frequency interval B_c over which the channel is approximately constant is referred to as the coherence bandwidth. Therefore, all frequency components of the signal experience the same magnitude of fading. Similarly, the coherence time T_c describes the time interval in which the channel response is almost constant. Each resource block that consists of a number of subcarriers and time samples where the channel response can be approximated as constant and flat fading is called a coherence block. A coherent block contains $\tau_c = B_c T_c$ complex-valued samples. Throughout this thesis, we assume that the channel realizations are independent between any pair of blocks which is known as the block fading assumption.

2.2 Line-of-Sight Channels

In this part, we define and explain features of an LoS channel. For the sake of argument, assume a propagation environment that is free from any reflectors or scatterers. The emitted waves travel in a direct path between the user and the base station. The base station is equipped with M antennas and the user has a single antenna. The antennas can be arranged according to different array geometries. The basic one is the uniform linear array (ULA) in which the antennas are evenly spaced on a straight line. The antenna spacing between antennas (in wavelengths) is denoted by d_H . Then, the spacing between two adjacent antennas is $d_H \lambda$ where λ is being the wavelength at the carrier frequency.

Suppose the user at a fixed location transmits the passband signal

$$s(t) = \text{Re} \{ u(t) e^{j2\pi f_c t} \} \quad (1)$$

where $u(t)$ is the complex baseband signal and f_c is the carrier frequency. The received signal at the m th antenna of the base station ULA is an attenuated and time delayed version of the transmitted signal where the time delay associated with the direct path between the user and the m th antenna is T_m . Then, ignoring the noise, it can be written as a convolution of the transmitted bandpass signal $s(t)$ and channel impulse response $h_m(t)$ as [26, Section 7.2]

$$\begin{aligned} r_m(t) &= (h_m * s)(t) = \text{Re} \left\{ \sqrt{\beta^m} u(t - T_m) e^{j2\pi f_c (t - T_m)} \right\} \\ &= \text{Re} \left\{ \left(\int_{-\infty}^{\infty} h_m(T) u(t - T) dT \right) e^{j2\pi f_c t} \right\} \end{aligned} \quad (2)$$

Figure 1: LoS propagation between a transmitting single antenna and a base station equipped with a ULA.

where “ $*$ ” denotes the convolution operator, The coefficient β^m describes the large-scale fading effects that account for dissipation of the transmit power over the distance between the base station antenna m and the user. Hence, the channel response of m th path is

$$h_m(t) = \sqrt{\beta^m} e^{-j2\pi f_c T_m} \delta(t - T_m) = \sqrt{\beta^m} e^{-j2\pi f_c \frac{d_m}{c}} \delta(t - T_m) \quad (3)$$

where c is the speed of light and d_m is the distance between the antenna m and the user. If d_m is larger than the Fraunhofer distance $\frac{2D^2}{\lambda}$, where D is the largest dimension of the antenna array, that defines the limit between the radiative near and far field regions, it is reasonable to assume that the incoming wave has a planar wavefront. Since the propagation distance is much larger than the size of the ULA at BS, we can write

$$d_m \approx d - (m - 1)d_H \lambda \sin(\varphi) \quad (4)$$

where d is the largest distance from the user to the base station and φ is the angle of incidence onto the antenna array as depicted in Figure 1. Then, in a coherence block, the channel response at the m th antenna is

$$h_m = \sqrt{\beta^m} e^{-\frac{j2\pi d}{\lambda}} e^{j2\pi d_H (m-1) \sin(\varphi)}. \quad (5)$$

The large-scale fading terms $\sqrt{\beta^m} e^{-\frac{j2\pi d}{\lambda}} = \sqrt{\beta}$, for all m , neglecting $e^{-\frac{j2\pi d}{\lambda}}$ since it takes an arbitrary value on the unit circle that is the same for all antennas and d is large compared to the size of ULA. Stacking the channel coefficients into a vector gives

$$\mathbf{h} = \sqrt{\beta} [1 e^{j2\pi d_H \sin(\varphi)} \dots e^{j2\pi d_H (M-1) \sin(\varphi)}]^T. \quad (6)$$

Figure 2: The function $g(\varphi_1, \varphi_2)$ versus the difference of the user angles for different number of ULA antennas where $d_H = 0.5$.

A massive MIMO base station is equipped with a massive number of antennas (e.g., a hundred), and it is able to serve multiple users thanks to its high resolution in the angular domain. To illustrate this property, suppose that the base station ULA is horizontally deployed. It serves two users that are located at the same elevation angle but the different azimuth angles φ_1 and φ_2 , respectively. The magnitude of the inner product of their channel vectors can be computed as

$$|\mathbf{h}_1^H(\varphi_1)\mathbf{h}_2(\varphi_2)| = \sqrt{\beta_1\beta_2}g(\varphi_1, \varphi_2) \quad (7)$$

where

$$g(\varphi_1, \varphi_2) = \left| \sum_{m=1}^M e^{j2\pi d_H(m-1)(\sin(\varphi_1) - \sin(\varphi_2))} \right|. \quad (8)$$

Using the identity $\sum_{n=0}^{N-1} q^n = \frac{1-q^N}{1-q}$ for $q \neq 1$, we obtain

$$g(\varphi_1, \varphi_2) = \left| \frac{1 - e^{j2\pi M d_H (\sin(\varphi_1) - \sin(\varphi_2))}}{1 - e^{j2\pi d_H (\sin(\varphi_1) - \sin(\varphi_2))}} \right| = \left| \frac{\sin(\pi M d_H (\sin(\varphi_1) - \sin(\varphi_2)))}{\sin(\pi d_H (\sin(\varphi_1) - \sin(\varphi_2)))} \right|. \quad (9)$$

From Figure 2, one can observe that the function $g(\varphi_1, \varphi_2)$ has the following properties:

- It has peaks at $\sin(\varphi_1) = \sin(\varphi_2)$: $g(\varphi_1, \varphi_2) = M$.
- $g(\varphi_1, \varphi_2) = 0$ at $\sin(\varphi_1) - \sin(\varphi_2) = \frac{m}{Md_H}$, for $m = 1, \dots, M - 1$.
- It is periodic with period $\frac{1}{d_H}$.

The values of $\sin(\varphi_1) - \sin(\varphi_2)$ are confined within an interval $[-2, 2]$. The main lobes of $g(\varphi_1, \varphi_2)$ have a width of $\frac{2}{Md_H}$ and they are centered around the integer multiples of $\frac{1}{d_H}$. Therefore, φ_1 and φ_2 are not distinguishable by the ULA whenever

$$|\sin(\varphi_1) - \sin(\varphi_2)| \ll \frac{1}{Md_H}. \quad (10)$$

for $d_H \leq 0.5$. The parameter $\frac{1}{Md_H}$ can be seen as a measure of resolvability in the angular domain. Note that it is inversely proportional to the width of the array, which means that massive MIMO has a good angular resolvability if it is wide. Another important point is that keeping the length of the ULA (proportional to Md_H) fixed and increasing the number of packed antennas does not increase the resolvability since it forces $d_H \rightarrow 0$.

2.3 Spatially Uncorrelated Rayleigh Fading

In the last subsection, we discussed an LoS channel model in a static free space environment which means that there was no scatterer or reflector in the propagation environment. Besides, both the user and the base station were static during transmission. These are rather extreme assumptions that rarely occur on Earth in practice. Nevertheless, it may be a good model in space.

In this subsection, we consider another extreme case: the uncorrelated Rayleigh fading model. Assume that we have the same base station and the user from the previous subsection. However, this time, we assume rich scattering conditions where the propagation environment contains many scatterers compared to the number of the base station antennas. In addition, the user and/or the scatterers may change their locations. Then, the transmitted signal from the user reaches the ULA through many different paths.

Suppose, for ease of notation, the mobile user sends an unmodulated carrier signal $s(t) = \text{Re} \{e^{j2\pi f_c t}\}$ to the base station equipped with the M antenna ULA. Note that $s(t)$ is narrowband for any multipath time delay spread. This signal propagates through a rich scattering environment with N multipath components. Then, neglecting the receiver noise, the received signal at the antenna m can be written as $r_m(t) = (h_m * s)(t) = \text{Re} \{h_m(t)e^{j2\pi f_c t}\}$ where $h_m(t)$ models the

effects of the propagation environment. It is the superposition of responses from all paths and can be described as [27, Chapter 3]

$$h_m(t) = \sum_{n=1}^N \alpha_{m,n} e^{-j\phi_{m,n}(t)} \delta(t - T_{m,n}) \quad (11)$$

where $\alpha_{m,n} \in \mathbb{R}$ is the channel gain, $T_{m,n}$ is the time delay and $\phi_{m,n}(t)$ accounts for the phase rotation associated with the n th path. The path gain $\alpha_{m,n}$ depends on the large scale effects such as the dissipation and absorption of the signal power over large distances, namely path loss and shadowing. On the other hand, the phase shift term $\phi_{m,n}(t)$ can change quickly, on the order of a signal wavelength, due to constructive and destructive additions of different multipath components. Thus, typically, $\alpha_{m,n}$ varies relatively slower than $\phi_{m,n}(t)$ and we assume that $\alpha_{m,n}$ is constant for many coherence blocks whereas $\phi_{m,n}(t)$ changes in every coherence block.

There are several effects that can cause the phase rotation. For example, even in free space when the user moves relative to the base station, the frequency of the propagating waves changes. More specifically, if the user (source of the waves) moves towards the base station, each successive wave front is emitted from a position closer to the base station. Therefore, the wavefront reaches the base station in less time. The time between the arrival of each successive wave crest is reduced i.e., the frequency is increased. Conversely, if the user moves away from the base station, each wave is emitted from a position farther from the base station than the previous wave, so the arrival time between successive waves is increased, reducing the frequency. This phenomena is called Doppler shift and here denoted with f_D . To quantify f_D , suppose in a time interval Δt , the change in the distance between the user and the base station is $\Delta d = v\Delta t \cos(\varphi)$ where v is the velocity of the user (assuming that it follows a linear trajectory) and φ is the angle of arrival to the base station relative to the direction of motion. The corresponding phase change due to this path length difference is $\Delta\phi_D = \frac{\Delta d}{\lambda} = \frac{2\pi v\Delta t \cos(\varphi)}{\lambda}$. Then, the Doppler frequency is obtained from the relation $f_D = \frac{1}{2\pi} \frac{\Delta\phi_D}{\Delta t} = \frac{v \cos(\varphi)}{\lambda}$. Throughout this section, we assume that v is changing slowly enough (i.e., small or zero acceleration) such that it is constant over the time interval of interest. If it is not the case, then $f_D(t)$ is a function of time and the corresponding Doppler phase shift becomes $\phi_D(t) = \int_0^t 2\pi f_D(t) dt$.

In a multipath environment, each scattering path may introduce a different amount of Doppler frequency shift, $f_{D_{m,n}} = \frac{v \cos(\varphi_{m,n})}{\lambda}$. The difference between the Doppler shifts of two paths is called the Doppler spread. The maximum of these differences is referred to as the maximum Doppler spread of the channel and here denoted by B_D . It is a measure of the channel frequency dispersion and inversely proportional to the channel coherence time $T_c \approx \frac{1}{B_D}$.

Another effect that can cause the phase rotation is the multipath time delays. To illustrate this behavior, suppose a carrier frequency $f_c = 3$ GHz and a multipath time delay associated to the path n and the antenna m , $T_{m,n} = 60$ ns (a typical value for an indoor environment). The resulting phase rotation is $2\pi f_c T_{m,n} = 0^\circ$. However, when this delay slightly changes, for example to $T_{m,n} = 60.5$ ns, the phase variation becomes 180° . Note that outdoor systems generally have much larger multipath delays than 60 ns, typically at the order of milliseconds. It shows that since f_c is generally large, a small change in $T_{m,n}$ can cause a rotation through 360° . Therefore, it is reasonable to assume that $2\pi f_c T_{m,n}$ is uniformly distributed on $[-\pi, \pi]$.

In addition to Doppler phase shifts and the multipath delays, the phase rotation term $\phi_{m,n}$ can have an initial phase offset ϕ_0 that stems from the oscillators at the transmitter and the receiver [28]. Therefore, we can model the phase rotation term as

$$\phi_{m,n}(t) = 2\pi f_c T_{m,n} + 2\pi f_{D_{m,n}} t + \phi_0. \quad (12)$$

To characterize the varying nature of the propagation environment, the path gain $\alpha_{m,n}$ and phase rotation $\phi_{m,n}(t)$ can be modeled as independent and identically distributed (i.i.d.) random variables [27]. If N is large enough, the central limit theorem implies that $h_m(t)$ is a circularly symmetric complex Gaussian variable and therefore the fading envelope $|h_m(t)|$ is Rayleigh distributed. Recall that a random variable Z is Rayleigh distributed (i.e., Rayleigh(σ)) if $Z = \sqrt{X^2 + Y^2}$ where $X \sim \mathcal{N}(0, \sigma^2)$ and $Y \sim \mathcal{N}(0, \sigma^2)$ are independent. The Rayleigh distribution has probability density function [29]

$$p_Z(z) = \frac{z}{\sigma^2} e^{-\frac{z^2}{2\sigma^2}}, \quad z \geq 0. \quad (13)$$

The early studies [30, 31] state that the Rayleigh distribution approximation is quite accurate when $N \geq 6$.

The i.i.d. Rayleigh fading channels appear under strict physical requirements. To illustrate this, consider a uniform scattering environment where many scatterers are densely packed with equally spaced angles on a sphere around the base station ULA. The uniform scattering environment model was first proposed by Clarke [32] and then popularized by Jakes [33]. In this environment, the received power from all scatterers are assumed to be equal which implies $\mathbb{E}\{\alpha_{m,n}^2\} = \frac{P_r}{N}$ where P_r is the total received power. This model implies that the channel vector $\mathbf{h}$ has no dominant spatial directivity since the signals are equally likely to arrive to the base station from any direction. Thus, each antenna receives an independent fading from other antennas i.e., $\mathbb{E}\{h_m^* h_s\} = 0$ for $s \neq m$. It leads the uncorrelated Rayleigh fading model

$$\mathbf{h} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_M, \beta \mathbf{I}_M) \quad (14)$$

where β accounts for the large-scale fading effects and the Gaussian distribution models the small-scale fading. With this model, the channel gain $\|\mathbf{h}\|^2$ is a scaled chi square distributed and is independent of the channel direction $\frac{\mathbf{h}}{\|\mathbf{h}\|}$ that is uniformly distributed over the unit sphere in $\mathbb{C}^M$ [6].

2.4 Spatially Correlated Rayleigh Fading

In the previous subsection, we discussed the i.i.d. Rayleigh fading model and assumed a uniform scattering environment in which the base station ULA was surrounded by a large number of scatterers. However, in practice, the base station is typically at an elevated position compared to the users at the ground. Thus, the base station rarely has scatterers in its close vicinity. In contrast, the scatterers are generally localized around the users and practical massive MIMO channels are spatially correlated as seen from measurement campaigns [34–36].

Suppose, as in the previous subsection, the ULA receives scattered signals from N different multipath components but this time the scatterers are concentrated around the user. The channel between the base station antenna m and the user is the superposition of responses from all paths and can be described as

$$h_m(t) = \sum_{n=1}^N \alpha_{m,n} e^{-j\phi_{m,n}(t)} \delta(t - T_{m,n}) \quad (15)$$

where $\alpha_{m,n} \in \mathbb{R}$ is the gain and $\phi_{m,n}(t)$ accounts for the phase rotation due to multipath delays, Doppler effect and initial phase offset associated with the n th path. We can rewrite (15) as

$$\begin{aligned} h_m(t) &= \sum_{n=1}^N \alpha_{m,n} e^{-j(2\pi f_c T_{m,n} + 2\pi f_{D_{m,n}} t + \phi_0)} \delta(t - T_{m,n}) \\ &\stackrel{(a)}{=} \sum_{n=1}^N \alpha_{m,n} e^{-j(2\pi f_{D_{m,n}} t + \phi_0)} e^{-j2\pi f_c \frac{d_{m,n}}{c}} \delta(t - T_{m,n}) \\ &\stackrel{(b)}{=} \sum_{n=1}^N \alpha_{m,n} e^{-j(2\pi f_{D_{m,n}} t + \phi_0 + 2\pi f_c \frac{d_n}{c})} e^{j2\pi f_c \frac{(m-1)d_H \lambda \sin(\bar{\varphi}_n)}{c}} \delta(t - T_{m,n}) \\ &\stackrel{(c)}{=} \sum_{n=1}^N g_n e^{j2\pi(m-1)d_H \sin(\bar{\varphi}_n)} \delta(t - T_{m,n}) \end{aligned} \quad (16)$$

where (a) follows from $T_{m,n} = \frac{d_{m,n}}{c}$ where $d_{m,n}$ is the distance between the antenna m and the user through n th path. In (b), using the far-field approximation in (4), we substitute $d_{m,n} \approx d_n - (m-1)d_H \lambda \sin(\bar{\varphi}_n)$ where d_n is the largest distance from the user to the ULA and $\bar{\varphi}_n$ is the angle of incidence onto the antenna array from the path

n . In (c), we note that the gain and phase rotations for each antenna is approximately the same since the size of the antenna array is much smaller than the propagation distance. Then, $\alpha_{m,n} \approx \alpha_n$ and we define $g_n = \alpha_n e^{-j(2\pi f_{D_{m,n}} t + \phi_0 + 2\pi f_c \frac{d_n}{c})}$ for all $m \in 1, \dots, M$.

Under the block flat fading assumption, we can drop the time index t and write the channel response $\mathbf{h} \in \mathbb{C}^M$ as

$$\mathbf{h} = \sum_{n=1}^N g_n [1, \dots, e^{j2\pi(m-1)d_H \sin(\bar{\varphi}_n)}, \dots, e^{j2\pi(M-1)d_H \sin(\bar{\varphi}_n)}]^T \quad (17)$$

where g_n represents both the gain and the phase rotation associated with the path n . Based on the same reasoning as in the previous sections, we can model g_n and the angle of arrivals $\bar{\varphi}_n$ as i.i.d. random variables. Suppose $\bar{\varphi}_n$ has probability density function $f(\bar{\varphi})$ and g_n has some distribution with zero-mean and variance $\mathbb{E}\{|g_n|^2\}$. The variance accounts for the average gain of the path n and the total average gain of the all multipath components is denoted by $\beta = \sum_{n=1}^N \mathbb{E}\{|g_n|^2\}$. As the number of multipaths $N \rightarrow \infty$, the multidimensional central theorem implies that

$$\mathbf{h} \rightarrow \mathcal{N}_{\mathbb{C}}(\mathbf{0}_M, \mathbf{R}) \quad (18)$$

where the convergence is in distribution and the (l, m) th element of correlation matrix $\mathbf{R}$ is

$$\begin{aligned} [\mathbf{R}]_{l,m} &= \sum_{n=1}^N \mathbb{E}\{|g_n|^2\} \mathbb{E}\{e^{j2\pi(l-1)d_H \sin(\bar{\varphi}_n)} e^{-j2\pi(m-1)d_H \sin(\bar{\varphi}_n)}\} \\ &= \beta \int e^{j2\pi(l-m)d_H \sin(\bar{\varphi})} f(\bar{\varphi}) d\bar{\varphi}. \end{aligned} \quad (19)$$

The correlation matrix $\mathbf{R}$ can be computed for any angle distribution $f(\bar{\varphi})$. From (19), we can observe that the integral only depends on the difference $l - m$, not on the individual values of l and m . It implies that $\mathbf{R}$ is a Toeplitz matrix.

The random arrival angle can be modeled as $\bar{\varphi} = \varphi + \delta$ where φ is the deterministic nominal arrival angle and δ is the random deviation from this angle with variance σ_φ^2 . The parameter σ_φ is called angular standard deviation (ASD) and it is a measure of how large the deviations from the nominal angle are. In literature, there are different assumptions on the distribution of δ . Mainly three probability distributions are studied: the uniformly distributed $\delta \sim \mathcal{U}[-\sigma_\varphi, \sigma_\varphi]$ [37–40], the Laplace distributed $\delta \sim \text{Lap}(0, \frac{\sigma_\varphi}{\sqrt{2}})$ [41, 42] and the Gaussian distributed $\delta \sim \mathcal{N}(0, \sigma_\varphi^2)$ [40, 43, 44].

The uniformly distributed δ is also called the one-ring model. It is assumed that the scatterers around the user are uniformly located on a ring as shown in Figure 3.

Figure 3: An illustration of the one-ring model.

If the user is d meters away from the base station and the ring has a radius r then $\sigma_\varphi \approx \arctan(\frac{r}{d})$. Then, the distribution of δ is

$$f(\delta) = \begin{cases} \frac{1}{2\sigma_\varphi}, & -\sigma_\varphi \leq \delta \leq \sigma_\varphi \\ 0, & \text{elsewhere.} \end{cases} \quad (20)$$

Inserting (20) into the integral (19) gives

$$[\mathbf{R}]_{l,m} = \beta \int_{-\sigma_\varphi}^{\sigma_\varphi} \frac{1}{2\sigma_\varphi} e^{j2\pi(l-m)d_H \sin(\varphi+\delta)} d\delta. \quad (21)$$

The closed-form expression for this integral utilizing Bessel functions is provided in [45]. It is worth noting that the one-ring model is different from the uniform scattering environment assumption in the uncorrelated Rayleigh fading case. In the one-ring model, the scatterers are in the vicinity of the user whereas the base station is surrounded by the scatterers in the latter.

Alternatively, with the Laplacian angular spread model $\delta \sim \text{Lap}(0, \frac{\sigma_\varphi}{\sqrt{2}})$, the probability density function $f(\delta) = \frac{1}{\sqrt{2}\sigma_\varphi} e^{-\frac{\sqrt{2}|\delta|}{\sigma_\varphi}}$ and the integral (19) becomes [42]

$$[\mathbf{R}]_{l,m} = \beta \int_{-\pi}^{\pi} \frac{1}{\sqrt{2}\sigma_\varphi} e^{-\frac{\sqrt{2}|\delta|}{\sigma_\varphi}} e^{j2\pi(l-m)d_H \sin(\varphi+\delta)} d\delta \quad (22)$$

and this integral can be numerically calculated. Note that $\mathbf{R}$ is a Toeplitz matrix, so that it is enough to compute the first column (or row) and then we know all the

entries. In the case of Gaussian angular spread model, $\delta \sim \mathcal{N}(0, \sigma_\varphi^2)$, the integral (19) is

$$[\mathbf{R}]_{l,m} = \beta \int e^{j2\pi(l-m)d_H \sin(\varphi+\delta)} \frac{1}{\sqrt{2\pi}\sigma_\varphi} e^{-\frac{\delta^2}{2\sigma_\varphi^2}} d\delta. \quad (23)$$

When the ASD is small enough ($\sigma_\varphi \leq 15^\circ$), $\sin(\delta) \approx \delta$ and $\cos(\delta) \approx 1$ [46] and we can approximately calculate (23) to reduce computational complexity as

$$\begin{aligned} [\mathbf{R}]_{l,m} &\approx \beta \int e^{j2\pi(l-m)d_H \sin(\varphi)} e^{j2\pi(l-m)d_H \cos(\varphi)\delta} \frac{1}{\sqrt{2\pi}\sigma_\varphi} e^{-\frac{\delta^2}{2\sigma_\varphi^2}} d\delta \\ &= \beta e^{j2\pi(l-m)d_H \sin(\varphi)} e^{-\frac{\sigma_\varphi^2}{2}(2\pi(l-m)d_H \cos(\varphi))^2} \int \frac{1}{\sqrt{2\pi}\sigma_\varphi} e^{-\frac{(\delta - j\sigma_\varphi^2 2\pi(l-m)d_H \cos(\varphi))^2}{2\sigma_\varphi^2}} d\delta \\ &= \beta e^{j2\pi(l-m)d_H \sin(\varphi)} e^{-\frac{\sigma_\varphi^2}{2}(2\pi(l-m)d_H \cos(\varphi))^2} \end{aligned} \quad (24)$$

where the last equality follows from $\int \frac{1}{\sqrt{2\pi}\sigma_\varphi} e^{-\frac{(\delta - j\sigma_\varphi^2 2\pi(l-m)d_H \cos(\varphi))^2}{2\sigma_\varphi^2}} d\delta = 1$. Note that in the extreme case of $\sigma_\varphi = 0$, the signal comes from a fixed direction (with angle of arrival φ) and the correlation matrix has rank 1. Conversely, as σ_φ grows off-diagonal elements of $\mathbf{R}$ go to zero and the rank increases.

The eigenstructure of $\mathbf{R}$ determines which spatial directions are statistically more likely to contain signal components than others. Suppose that $\mathbf{R}$ has the eigenvalue decomposition $\mathbf{R} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$ where $\mathbf{\Lambda} \in \mathbb{R}^{r \times r}$ is a diagonal matrix containing $r = \text{rank}(\mathbf{R})$ non-zero eigenvalues of $\mathbf{R}$ and $\mathbf{U} \in \mathbb{C}^{M \times r}$ consists of the associated eigenvectors such that $\mathbf{U}^H \mathbf{U} = \mathbf{I}_r$. Then, using the Karhunen-Loève representation [47], we can write the channel vector $\mathbf{h}$ as

$$\mathbf{h} = \mathbf{R}^{1/2} \mathbf{w} = \mathbf{U} \mathbf{\Lambda}^{1/2} \mathbf{U}^H \mathbf{w} \sim \mathbf{U} \mathbf{\Lambda}^{1/2} \hat{\mathbf{w}} \quad (25)$$

where $\mathbf{w} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_M, \mathbf{I}_M)$ and $\hat{\mathbf{w}} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}_r, \mathbf{I}_r)$. In the last step, " $\sim$ " implies that the distributions of $\mathbf{h}$ and $\mathbf{U} \mathbf{\Lambda}^{1/2} \hat{\mathbf{w}}$ are identical. This representation is a convenient way to generate fading realizations of a spatially correlated channel.

According to the Szegö's theorem, the Toeplitz matrix $\mathbf{R}$ becomes asymptotically equivalent to a circulant matrix as $M \rightarrow \infty$ [48]. Then, its eigenvector matrix is equal to the unitary discrete Fourier transform (DFT) matrix $\mathbf{F} \in \mathbb{C}^{M \times M}$ with elements

$$[\mathbf{F}]_{l,m} = \frac{1}{\sqrt{M}} e^{j\frac{2\pi}{M}(l-1)(m-1)} \quad (26)$$

for $l, m \in 1, \dots, M$. $\mathbf{F}$ corresponds to a collection of beams in different angular directions. In the regime of a large number of antennas, we can approximate $\mathbf{U}$ in (25) with $\bar{\mathbf{F}} \in \mathbb{C}^{M \times r}$ that is a submatrix formed by selection of r columns from $\mathbf{F}$.

Figure 4: Normalized eigenvalues of the spatial correlation matrix $\mathbf{R}$ where $\text{tr}(\mathbf{R}) = M$ with $M = 100$, nominal angle $\varphi = 30^\circ$ and standard deviations $\sigma_\varphi = [10^\circ, 30^\circ]$. The uncorrelated fading is added as a reference where $\mathbf{R} = \mathbf{I}_M$.

Thus, $\mathbf{R} \approx \bar{\mathbf{F}}\mathbf{\Lambda}\bar{\mathbf{F}}^H$ and this can also be used to generate spatially correlated fading realizations instead of the Karhunen-Loève representation. The diagonal matrix $\mathbf{\Lambda}$ assigns power to these directions. If the antennas in the ULA are critically spaced i.e., $d_H = 0.5$ then $\bar{\mathbf{F}}^H \mathbf{h}$ is equivalent to the angular domain representation [26, Chapter 7.3.3].

As shown in Figure 4, higher spatial correlation creates larger eigenvalue variations. High levels of spatial correlation occurs when σ_φ is small. In the case of $\sigma_\varphi = 10^\circ$, $\mathbf{R}$ has a low rank since almost 60% of the eigenvalues are negligibly small compared to others. It means that the propagation environment has some dominant spatial eigenvectors corresponding to the beams in the directions around the user. As σ_φ grows, the spatial directions spread and variation in the eigenvalues becomes smaller. In the uncorrelated fading case, $\mathbf{R}$ is full-rank and has no spatial directivity.

The local scattering channel models discussed above are mathematically convenient and easy to simulate while still capturing essential characteristics of the wireless channel between the base station equipped with large antenna arrays and single-antenna users. However, these models may be insufficient for large-scale system-level simulations with the goal of quantifying the real-world performance of MIMO systems. In particular, it is not realistic to assume a single local cluster of

scatterers around the user. For this reason, the 3rd Generation Partnership Project (3GPP) has defined a 3D stochastic geometry-based channel model for MIMO systems [49], which explicitly accounts for multiple spatial clusters of scatterers and a mix of NLoS and LoS propagation paths. In Paper A, based on the 3GPP model in [49], we consider $N_c = 6$ disjoint scattering clusters where each cluster is modeled by the (approximate) Gaussian local scattering model such that

$$[\mathbf{R}]_{l,m} = \frac{\beta}{N_c} \sum_{n=1}^{N_c} e^{j2\pi(l-m)d_H \sin(\varphi_n)} e^{-\frac{\sigma_\varphi^2}{2} (2\pi(l-m)d_H \cos(\varphi_n))^2}, \quad (27)$$

where $\varphi_n \sim \mathcal{U}[\varphi - 40^\circ, \varphi + 40^\circ]$ is the nominal AoA for the n cluster. The multipath components of a cluster have Gaussian distributed AoAs, distributed around the nominal AoA with the ASD $\sigma_\varphi = 5^\circ$.

2.5 Spatially Correlated Rician Fading

The i.i.d. Rayleigh fading or free-space LoS channel models are widely used in massive MIMO research since they enable tractable performance analysis. However, practical channels can consist of a combination of an LoS path and a correlated small-scale fading component caused by a finite number of scattering clusters. In this subsection, we consider the spatially correlated Rician fading model that accounts for these effects.

Suppose that the base station is equipped with the ULA and the mobile user has a single antenna as before. In this case, the propagation channel between the base station and the user can be modeled as

$$\mathbf{h} = \bar{\mathbf{h}}e^{j\theta} + \mathbf{g} \quad (28)$$

where $\bar{\mathbf{h}}e^{j\theta} \in \mathbb{C}^M$ corresponds to the LoS component and $\mathbf{g} \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R})$ accounts for the non-line-of-sight (NLoS) (often referred to as diffuse) components. The macroscopic propagation effects of the LoS is described by the term $\bar{\mathbf{h}} \in \mathbb{R}^M$ and the phase rotation is denoted by $e^{j\theta}$.

Each element of $\mathbf{h}$ is denoted by h_m for $m \in \{1, \dots, M\}$ and the channel envelope $|h_m|$ is Rice distributed. The channel model of $\mathbf{h}$ is named after Stephan O. Rice as Rician or Ricean fading. In the literature, there is no agreement on the spelling. Today, a Google scholar search gives 55.2k results for “Rician” and 14.9k for “Ricean”. Therefore, we preferred to use “Rician” in this thesis.

A random variable Z is Rice distributed (i.e., $Z \sim \text{Rice}(|v|, \sigma)$) if $Z = \sqrt{X^2 + Y^2}$ where $X \sim \mathcal{N}(v \cos(\theta), \sigma^2)$ and $Y \sim \mathcal{N}(v \sin(\theta), \sigma^2)$ are independent and θ is any real number [50]. For these parameters, the probability density

function is given by [50]

$$p_Z(z) = \frac{z}{\sigma^2} e^{-\frac{(z^2+v^2)}{2\sigma^2}} I_0\left(\frac{zv}{\sigma^2}\right), \quad z \geq 0 \quad (29)$$

where I_0 is the modified Bessel function of the first kind with order zero. The total average received power in the Rician fading can be calculated by

$$P = \int_0^\infty z^2 p_Z(z) dz = 2\sigma^2 + v^2. \quad (30)$$

From (29), we can observe that the LoS phase θ does not affect the distribution. Adopting the notation for the channel h_m gives that $2\sigma^2 = \beta = \frac{1}{M} \text{tr}(\mathbf{R})$ is the average channel gain of NLoS multipath components at the antenna m and $v^2 = \bar{h}_m^2$ is the power in the LoS component. The ratio of the power in the LoS component to the power in the NLoS component is denoted by the Rician factor κ . It is equal to $\kappa = \frac{\bar{h}_m^2}{\beta}$ and shows the level of fading. The portion of the power that the LoS path contains is $\bar{h}_m^2 = \frac{\kappa P}{\kappa+1}$ and the NLoS part has the power $\beta = \frac{P}{\kappa+1}$. Note that for $\kappa = 0$, we have Rayleigh fading since there is no power in the LoS path. Conversely, if $\kappa \rightarrow \infty$ we have no multipath meaning that there is only the LoS component. It shows that a small κ implies severe fading whereas a larger κ implies a milder fading. The 3GPP model in [49] gives the Rician factor as $\kappa = 13 - 0.03d$ [dB] where d is the distance between the base station and the user in meters.

To simplify the analysis, the LoS phase shift θ and the spatial correlation are often neglected. The LoS phase is typically assumed to be fixed or can be tracked perfectly. As discussed above, neglecting the phase shift does not change the distribution of the envelope. However, the resulting model becomes physically less accurate. In Paper A, we considered a co-located massive MIMO system where the LoS phase is identical for all base station antennas and may therefore be accurately tracked in practice. In co-located MIMO systems, the LoS phase can be estimated by employing classical algorithms such as estimation of signal parameters via rotational invariance techniques (ESPRIT) [51] and multiple signal classification (MUSIC) [52]. However, these methods either require multiple antennas and/or long sample sequences (snapshots). In Paper B, we studied a cell-free massive MIMO system where each access point has a single antenna. Consequently, it is harder to estimate the LoS phase. In a low mobility scenario in which the access points are equipped with multiple antennas, the phase-shifts can be estimated quite well, but the estimates will anyway be imperfect since the estimation resources are practically limited. In Paper B, to see the effect of the phase shift on system performance, we studied two cases where the phase is either known or completely unknown.

2.6 Impact of LoS path and Spatial Correlation in Massive MIMO

In this section, we will demonstrate the basic impacts of LoS path and spatial correlation on the communication performance in massive MIMO. In early single-user MIMO research, spatial correlation is viewed as a detrimental effect [53, 54] since the spatial correlation matrix has a lower rank compared to the uncorrelated case as depicted in Figure 4. However, it may not be the case in the multiuser massive MIMO communications. The spatial correlation can be both beneficial and detrimental depending on the relation between the dominant eigenvectors of the active users. Similarly, in some cases such as when the AoAs of two users are not distinct enough to be resolved by the base station, the existence of an LoS paths can be detrimental as well [55]. In this case, these users can be dropped by using a scheduling scheme. To understand the effects of the spatial correlation and the LoS path, we first visit two key properties of massive MIMO: channel hardening and favorable propagation.

A random propagation channel $\mathbf{h}$ provides channel hardening if

$$\frac{\|\mathbf{h}\|^2}{\mathbb{E}\{\|\mathbf{h}\|^2\}} \rightarrow 1 \quad (31)$$

as $M \rightarrow \infty$. It implies that the value of the instantaneous channel gain $\|\mathbf{h}\|^2$ is close to its mean value $\mathbb{E}\{\|\mathbf{h}\|^2\}$ when the number of antennas is quite large. In other words, as more antennas are added the channel variations reduce. However, it does not mean that $\|\mathbf{h}\|^2 \rightarrow \mathbb{E}\{\|\mathbf{h}\|^2\}$ since both terms generally diverge as $M \rightarrow \infty$. We can quantify how close we are to the asymptotic channel hardening when we have practical number of antennas by calculating $\text{Var}\left\{\frac{\|\mathbf{h}\|^2}{\mathbb{E}\{\|\mathbf{h}\|^2\}}\right\}$. If the variance goes to zero as $M \rightarrow \infty$, we obtain convergence in probability. Using Lemma 5 from Paper A, for spatially correlated Rician fading channels, we can obtain

$$\begin{aligned} \text{Var}\left\{\frac{\|\mathbf{h}\|^2}{\mathbb{E}\{\|\mathbf{h}\|^2\}}\right\} &= \mathbb{E}\left\{\left(\frac{\|\mathbf{h}\|^2}{\mathbb{E}\{\|\mathbf{h}\|^2\}}\right)^2\right\} - \left(\mathbb{E}\left\{\frac{\|\mathbf{h}\|^2}{\mathbb{E}\{\|\mathbf{h}\|^2\}}\right\}\right)^2 \\ &= \frac{\mathbb{E}\{\|\mathbf{h}\|^4\} - (\mathbb{E}\{\|\mathbf{h}\|^2\})^2}{(\mathbb{E}\{\|\mathbf{h}\|^2\})^2} = \frac{\text{tr}(\mathbf{R}^2) + 2\text{Re}\{\bar{\mathbf{h}}^H \mathbf{R} \bar{\mathbf{h}}\}}{(\text{tr}(\mathbf{R}) + \|\bar{\mathbf{h}}\|^2)^2} \end{aligned} \quad (32)$$

and it should be close to zero if channel hardening is to be observed. In the special case of i.i.d. Rayleigh fading, $\mathbf{R} = \beta \mathbf{I}_M$ (32) becomes $\frac{\text{tr}(\mathbf{R}^2)}{(\text{tr}(\mathbf{R}))^2} = \frac{1}{M}$. Similarly, for i.i.d. Rician fading with $\|\bar{\mathbf{h}}\|^2 = \beta^{\text{los}} M$, the variance in (32) is

$$\frac{1}{M} \frac{\beta^2 + 2\beta\beta^{\text{los}}}{\beta^2 + 2\beta\beta^{\text{los}} + (\beta^{\text{los}})^2} = \frac{1}{M} \frac{2\kappa + 1}{\kappa^2 + 2\kappa + 1} \quad (33)$$

using the definition of Rician factor $\kappa = \frac{\beta^{\text{los}}}{\beta}$. Figure 5 compares the variance of channel hardening defined in (32) as a function of the number of antennas for different channel models. Here the covariance matrices are normalized such that $\text{tr}(\mathbf{R}) = M$ for both correlated and i.i.d. fading. Likewise, the LoS path is normalized as $\|\bar{\mathbf{h}}\|^2 = M$. Note that this normalization gives a Rician factor $\kappa = 1$. As can be observed from the figure, the existence of LoS improves the channel hardening. It should be noted that $\kappa = 1$ implies rather severe fading and as κ increases the gap between Rayleigh and Rician models will increase as well. In addition, we can observe that spatial correlation reduces the channel hardening since the eigenvalue variations in $\mathbf{R}$ increase. To summarize, spatial correlation reduces and the LoS path increases the level of channel hardening.

Figure 5: Variance of channel hardening defined in (32) as a function of the number of antennas. Correlated fading is generated using local scattering model with the nominal angle $\varphi = 30^\circ$, ASD 10° and Gaussian angular distribution.

Another key property of massive MIMO, favorable propagation, implies that the propagation channel responses from the base station to two distinct users point in sufficiently different directions. In other words, the favorable propagation makes the directions of two users channels asymptotically orthogonal. This property helps the base station to mitigate interference between the users, without losing much in desired signal power. Assume that the channels of the users are denoted by $\mathbf{h}_1$ and $\mathbf{h}_2$, respectively. The pair of channels $\mathbf{h}_1$ and $\mathbf{h}_2$ provide asymptotically favorable

propagation if

$$\frac{\mathbf{h}_1^H \mathbf{h}_2}{\sqrt{\mathbb{E}\{\|\mathbf{h}_1\|^2\} \mathbb{E}\{\|\mathbf{h}_2\|^2\}}} \rightarrow 0 \quad (34)$$

as $M \rightarrow \infty$. Similar to channel hardening discussion, we can quantify how close we are to asymptotic favorable propagation with practical number of antennas by calculating $\text{Var} \left\{ \frac{\mathbf{h}_1^H \mathbf{h}_2}{\sqrt{\mathbb{E}\{\|\mathbf{h}_1\|^2\} \mathbb{E}\{\|\mathbf{h}_2\|^2\}}} \right\}$. Using Lemma 4 from Paper A, for spatially correlated Rician fading channels, we can calculate

$$\begin{aligned} & \text{Var} \left\{ \frac{\mathbf{h}_1^H \mathbf{h}_2}{\sqrt{\mathbb{E}\{\|\mathbf{h}_1\|^2\} \mathbb{E}\{\|\mathbf{h}_2\|^2\}}} \right\} \\ &= \frac{\text{tr}(\mathbf{R}_1 \mathbf{R}_2) + \text{Re}\{\bar{\mathbf{h}}_2^H \mathbf{R}_1 \bar{\mathbf{h}}_2\} + \text{Re}\{\bar{\mathbf{h}}_1^H \mathbf{R}_2 \bar{\mathbf{h}}_1\} + |\bar{\mathbf{h}}_1^H \bar{\mathbf{h}}_2|^2}{(\text{tr}(\mathbf{R}_1) + \|\bar{\mathbf{h}}_1\|^2)(\text{tr}(\mathbf{R}_2) + \|\bar{\mathbf{h}}_2\|^2)} \end{aligned} \quad (35)$$

and it should be close to zero if favorable propagation is to be observed.

Figure 6: Variance of favorable propagation for $M = 100$ and ASD 10° (with Gaussian angular distribution) if a correlated channel model is used. The user 1 has a nominal angle of 60° , while the angle of the interfering user (the user 2) is varied $[0^\circ, 180^\circ]$.

Figure 6 compares the levels of favorable propagation for different channel models. It shows that the effect of the LoS path is quite prominent if the users have similar nominal angles. This is also evident from (9) since the base station is not

able to distinguish the channels of users with similar angles. From Figure 2, we can deduce that these peaks will get narrower as the number of antennas increase since the resolution of ULA will increase. Moreover, we observe that spatial correlation increases the levels of favorable propagation if the covariance matrices of the users are different enough.

Chapter 3

Basics of Massive MIMO

In this section, we describe some of the fundamental concepts in massive MIMO technology. Our aim is to walk through the foundations of massive MIMO that the included research papers in the thesis are built upon. For more in-depth discussions, readers are referred to [5, 6].

3.1 Duplexing Protocol

As described in Chapter 2, fading channels vary over time and frequency. Recall that in the block fading model, time and frequency resources are divided into the coherence blocks wherein the channel is time invariant and frequency flat. Moreover, it is assumed that the channel realizations are independent between any pair of blocks. These coherence blocks are mainly utilized for data transmission and channel estimation to enable data transmission. The transmission from a base station to a user is called downlink transmission, whereas uplink transmission is from a user to a base station.

The uplink and downlink transmissions can be separated either in time or frequency as illustrated in Figure 1. In time-division duplex (TDD) mode, the uplink and downlink transmissions are separated in time while using the whole coherence bandwidth. In this case, the channels are reciprocal meaning that the uplink and downlink channels of a base station and user antenna pair are the same. By leveraging the channel reciprocity property, it is sufficient to estimate the channels only in the uplink. The channel estimation is performed by sending some predefined deterministic pilot sequences that are known at both the base station and users. If we consider a scenario where a base station equipped with M antennas serves K single antenna users, the amount of coherence block resources that should be allocated to channel estimation is K samples. Notice that the number of required pilot signals is independent of the number of base station antennas. The task of channel estimation

Figure 1: Time and frequency separation of coherence blocks in TDD and FDD protocols

is carried out in the uplink phase since $M > K$ in massive MIMO.

On the other hand, in frequency-division duplex (FDD) mode, the bandwidth is split between the uplink and downlink transmissions. In general, the uplink and downlink bands are not next to each other but separated by approximately 100 MHz, to avoid interference. Therefore, the channel reciprocity does not hold due to frequency selective fading. Consequently, both the uplink and downlink channels are needed to be estimated. The base station sends pilot signals to the users, and the channel estimation is carried out at the user side. Then, the estimated channels are fed back to the base station over a control channel. To estimate the uplink channels, the base station processes the pilot signals transmitted by the users. In contrast to TDD operation, the number of dedicated pilot resources is not independent of M . As a result, TDD is the mode of operation that stands out in massive MIMO.

Figure 2: Illustration of a basic TDD transmission protocol.

To present the basic properties of massive MIMO, we consider a single-cell system with M base station antennas and K single antenna users. The system operates in TDD mode. Each TDD coherence block consists of $\tau_c = B_c T_c$ samples as illustrated in Figure 2. In a massive MIMO system, the coherence block is split into three phases: uplink channel estimation, uplink data transmission, and downlink data transmission. The pilot based channel estimation procedure is described in the following section.

3.2 Channel Estimation

The channel estimates are essential to beamform the signals effectively. Accordingly, $\tau_p \geq K$ signals are reserved for the uplink pilot based channel estimation giving room for τ_p mutually orthogonal pilot sequences. The deterministic pilot sequence of user $k \in 1, \dots, K$ is denoted by $\phi_k \in \mathbb{C}^{\tau_p \times 1}$ where $\|\phi_k\|^2 = \tau_p$ and $\phi_k^H \phi_l = 0$ if $l \neq k$. The elements of ϕ_k are scaled by the pilot power $\sqrt{p_k}$ and then transmitted to the base station. The received signal $\mathbf{Y}^p \in \mathbb{C}^{M \times \tau_p}$ at the base station is

$$\mathbf{Y}^p = \sum_{l=1}^K \sqrt{p_l} \mathbf{h}_l \phi_l^T + \mathbf{N}^p \quad (36)$$

where $\mathbf{N}^p \in \mathbb{C}^{M \times \tau_p}$ is the independent additive receiver noise with i.i.d. elements distributed $\mathcal{N}_{\mathbb{C}}(0, \sigma_{\text{ul}}^2)$. The channels of users are modeled by spatially correlated Rayleigh fading as $\mathbf{h}_k \sim \mathcal{N}_{\mathbb{C}}(\mathbf{0}, \mathbf{R}_k)$ which was described in Section 2.4. The received signal $\mathbf{Y}^p$ consists of the observations of all the channel responses and noise. If the base station wants to estimate the channel of user k then it multiplies the corresponding pilot sequence ϕ_k with $\mathbf{Y}^p$ to exploit the assumed orthogonality between the sequences. Then, the processed received signal becomes

$$\mathbf{y}_k^p = \mathbf{Y}^p \phi_k^* = \sqrt{p_k} \tau_p \mathbf{h}_k + \mathbf{N}^p \phi_k^* \quad (37)$$

where the first term is the desired signal and the second term is the noise $\mathbf{N}^p \phi_k^* \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_{\text{ul}}^2 \tau_p \mathbf{I}_M)$. Then, we notice that $\mathbf{y}_k^p$ is the sufficient statistics to estimate the channel $\mathbf{h}_k$ since there is no loss in the useful information compared to the original received signal $\mathbf{Y}^p$ [56]. Based on (37), the base station can apply the minimum mean square error (MMSE) estimator to acquire the channel estimate $\hat{\mathbf{h}}_k$ that minimizes the mean square error (MSE) $\mathbb{E} \{ \|\mathbf{h}_k - \hat{\mathbf{h}}_k\|^2 \}$. Then, the MMSE estimate $\hat{\mathbf{h}}_k$ is given by [6, Theorem 3.1]

$$\hat{\mathbf{h}}_k = \sqrt{p_k} \mathbf{R}_k \mathbf{\Psi}_k \mathbf{y}_k^p \quad (38)$$

where

$$\mathbf{\Psi}_k = (p_k \tau_p \mathbf{R}_k + \sigma_{\text{ul}}^2 \mathbf{I}_M)^{-1}. \quad (39)$$

In addition, the channel estimation error vector $\tilde{\mathbf{h}}_k = \mathbf{h}_k - \hat{\mathbf{h}}_k$ has the covariance matrix $\mathbf{C}_k = \mathbb{E} \{ \tilde{\mathbf{h}}_k \tilde{\mathbf{h}}_k^H \}$, given by

$$\mathbf{C}_k = \mathbf{R}_k - p_k \tau_p \mathbf{R}_k \boldsymbol{\Psi}_k \mathbf{R}_k. \quad (40)$$

Then, the MSE that represents the estimation quality is equal to $\mathbb{E} \{ \|\mathbf{h}_k - \hat{\mathbf{h}}_k\|^2 \} = \text{tr}(\mathbf{C}_k)$. Smaller values of MSE correspond to good estimation quality. These channel estimates are utilized in the data transmission as described in the following subsection.

3.3 Uplink Data Transmission

In the uplink transmission, user k transmits a data signal $s_k \sim \mathcal{N}_{\mathbb{C}}(0, p_k)$ to the base station where the variance p_k is the data transmit power. Then, the received signal $\mathbf{y} \in \mathbb{C}^{M \times 1}$ at the base station is

$$\begin{aligned} \mathbf{y} &= \sum_{l=1}^K \mathbf{h}_l s_l + \mathbf{n} \\ &= \underbrace{\mathbf{h}_k s_k}_{\text{Desired signal}} + \underbrace{\sum_{l \neq k} \mathbf{h}_l s_l}_{\text{Interference}} + \underbrace{\mathbf{n}}_{\text{Noise}} \end{aligned} \quad (41)$$

where $\mathbf{n} \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_{\text{ul}}^2 \mathbf{I}_M)$ is the independent additive receiver noise. Thanks to the favorable propagation property of massive MIMO systems, linear signal processing schemes are nearly optimal. To decode the data signal from user k , the base station applies a receive combining vector $\mathbf{v}_k \in \mathbb{C}^{M \times 1}$ to separate the desired signal from the interference as

$$\mathbf{v}_k^H \mathbf{y} = \mathbf{v}_k^H \mathbf{h}_k s_k + \sum_{l \neq k} \mathbf{v}_k^H \mathbf{h}_l s_l + \mathbf{v}_k^H \mathbf{n} \quad (42)$$

$$\begin{aligned} &= \underbrace{\mathbf{v}_k^H \hat{\mathbf{h}}_k s_k}_{\text{Desired signal over estimated channel}} + \underbrace{\mathbf{v}_k^H \tilde{\mathbf{h}}_k s_k}_{\text{Desired signal over unknown channel}} \\ &+ \underbrace{\sum_{l \neq k} \mathbf{v}_k^H \mathbf{h}_l s_l}_{\text{Interference}} + \underbrace{\mathbf{v}_k^H \mathbf{n}}_{\text{Noise}}. \end{aligned} \quad (43)$$

The receive combining vectors are formed based on the available channel estimates from the uplink pilot transmission. To be more specific, the MMSE combining vector utilizing the channel estimates and channel estimation error covariance matrices is defined as

$$\mathbf{v}_k^{\text{MMSE}} = p_k \left(\sum_{l=1}^K p_l \hat{\mathbf{h}}_l \hat{\mathbf{h}}_l^H + p_l \mathbf{C}_l + \sigma_{\text{ul}}^2 \mathbf{I}_M \right)^{-1} \hat{\mathbf{h}}_k. \quad (44)$$

Also, a simple and popular choice that maximizes the ratio $\frac{\mathbf{v}_k^H \hat{\mathbf{h}}_k}{\|\mathbf{v}_k\|^2}$ is called maximum ratio (MR) combining and defined as

$$\mathbf{v}_k^{\text{MR}} = \hat{\mathbf{h}}_k. \quad (45)$$

If the base station prioritizes to cancel the interference caused by other users, it might use the zero-forcing (ZF) combining vector

$$\mathbf{v}_k^{\text{ZF}} = \left[\hat{\mathbf{H}} \left(\hat{\mathbf{H}}^H \hat{\mathbf{H}} \right)^{-1} \right]_k \quad (46)$$

where $\hat{\mathbf{H}} = [\hat{\mathbf{h}}_1, \dots, \hat{\mathbf{h}}_K]$ and $[\cdot]_k$ denotes the k th column of the matrix. If the channels are perfectly known, then ZF vector correspond to projecting the received signal of desired user k onto the null space of other users' channels. Note that this operation requires $M > K$.

If the MMSE estimator in (38) is used, then the uplink channel capacity of user k is lower bounded by SE_k^{ul} [bps/Hz] as given in [6]

$$\text{SE}_k^{\text{ul}} = \frac{\tau_c - \tau_p}{\tau_c} \mathbb{E} \left\{ \log_2 (1 + \text{SINR}_k^{\text{ul}}) \right\} \quad (47)$$

with

$$\text{SINR}_k^{\text{ul}} = \frac{p_k |\mathbf{v}_k^H \hat{\mathbf{h}}_k|^2}{\sum_{l \neq k} p_l |\mathbf{v}_k^H \hat{\mathbf{h}}_l|^2 + \mathbf{v}_k^H \left(\sum_{l=1}^K p_l \mathbf{C}_l + \sigma_{\text{ul}}^2 \mathbf{I}_M \right) \mathbf{v}_k} \quad (48)$$

where the expectation is with respect to the side information, i.e., the channel estimates. The spectral efficiency (SE) expression holds for any choice of combining vector $\mathbf{v}_k$ as long as the MMSE estimator is used for the channel estimation. The SINR expression in (48) is a random variable that takes a new independent realization at each coherence block. The closed-form expressions are useful when building signal processing algorithms and the expectation in (47) is generally hard to compute in closed-form.

Another bound that leads to closed-form expressions and therefore, commonly used in the literature is the use-and-then-forget (UatF) bound [5]. The name comes from the idea that the channel estimates are used in the receive combining but then forgotten before the signal detection. We rewrite (42) as

$$\mathbf{v}_k^H \mathbf{y} = \mathbb{E} \left\{ \mathbf{v}_k^H \mathbf{h}_k \right\} s_k + (\mathbf{v}_k^H \mathbf{h}_k - \mathbb{E} \left\{ \mathbf{v}_k^H \mathbf{h}_k \right\}) s_k + \sum_{l \neq k} \mathbf{v}_k^H \mathbf{h}_l s_l + \mathbf{v}_k^H \mathbf{n} \quad (49)$$

by adding and subtracting $\mathbb{E} \left\{ \mathbf{v}_k^H \mathbf{h}_k \right\} s_k$. The desired signal received over the averaged combined channel $\mathbb{E} \left\{ \mathbf{v}_k^H \mathbf{h}_k \right\}$ is treated as the true desired signal. The part

received over $\mathbf{v}_k^H \mathbf{h}_k - \mathbb{E} \{ \mathbf{v}_k^H \mathbf{h}_k \}$ is treated as uncorrelated noise. It is hard to compute (47) since the expectation is in front of the logarithm, which is caused by having a random channel. By using the trick in (49), we treat channel as deterministic and equal to $\mathbb{E} \{ \mathbf{v}_k^H \mathbf{h}_k \}$. This bound will work well if the variations around the mean are small. In this case, the lower bound on the capacity of user k is $\underline{\text{SE}}_k^{\text{ul}} = \frac{\tau_c - \tau_p}{\tau_c} \log_2(1 + \underline{\text{SINR}}_k^{\text{ul}})$ with

$$\underline{\text{SINR}}_k^{\text{ul}} = \frac{p_k |\mathbb{E} \{ \mathbf{v}_k^H \mathbf{h}_k \}|^2}{\sum_{l=1}^K p_l \mathbb{E} \{ |\mathbf{v}_k^H \mathbf{h}_l|^2 \} - p_k |\mathbb{E} \{ \mathbf{v}_k^H \mathbf{h}_k \}|^2 + \sigma_{\text{ul}}^2 \mathbb{E} \{ \|\mathbf{v}_k\|^2 \}} \quad (50)$$

where the expectations are with respect to all sources of randomness. This bound is less tight than in (47) since the channel estimates are discarded in the signal detection.

3.4 Downlink Data Transmission

In the downlink transmission, the base station sends data signals simultaneously to all users using precoding vectors $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ that are computed based on the channel estimates as $\mathbf{w}_k = \frac{\mathbf{v}_k}{\sqrt{\mathbb{E} \{ \|\mathbf{v}_k\|^2 \}}}$ where $\mathbf{v}_k$ is defined in Section 3.3. The transmitted downlink signal is

$$\mathbf{x} = \sum_{l=1}^K \mathbf{w}_l d_l \quad (51)$$

where $d_l \sim \mathcal{N}_{\mathbb{C}}(0, \rho_l)$ is the data signal with transmit power ρ_l . The precoding vector determines the spatial directivity and satisfies $\mathbb{E} \{ \|\mathbf{w}_k\|^2 \} = 1$. Then, the received signal at the user k is

$$\begin{aligned} y_k &= \mathbf{h}_k^H \mathbf{x} + n_k \\ &= \underbrace{\mathbf{h}_k^H \mathbf{w}_k d_k}_{\text{Desired Signal}} + \underbrace{\sum_{l \neq k} \mathbf{h}_k^H \mathbf{w}_l d_l}_{\text{Interference}} + \underbrace{n_k}_{\text{Noise}} \end{aligned} \quad (52)$$

where $n_k \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_{\text{dl}}^2)$ is the additive receiver noise. Since there is no downlink pilot transmission, the user do not have the instantaneous channel state information. To decode the received signal at the user k , we assume that the user k knows the averaged precoded channel $\mathbb{E} \{ \mathbf{h}_k^H \mathbf{w}_k \}$. Therefore, we can rewrite (52) as

$$y_k = \underbrace{\mathbb{E} \{ \mathbf{h}_k^H \mathbf{w}_k \} d_k}_{\text{Desired signal over average channel}} + \underbrace{(\mathbf{h}_k^H \mathbf{w}_k - \mathbb{E} \{ \mathbf{h}_k^H \mathbf{w}_k \}) d_k}_{\text{Desired signal over unknown channel}} + \underbrace{\sum_{l \neq k} \mathbf{h}_k^H \mathbf{w}_l d_l}_{\text{Interference}} + \underbrace{n_k}_{\text{Noise}}. \quad (53)$$

Treating the first term as the desired signal and the rest of the terms as uncorrelated noise, the following capacity lower bound, called hardening bound, can be obtained [6]. The downlink achievable SE of user k is $\underline{\text{SE}}_k = \frac{\tau_c - \tau_p}{\tau_c} \log_2(1 + \underline{\text{SINR}}_k^{\text{dl}})$ with

$$\underline{\text{SINR}}_k^{\text{dl}} = \frac{\rho_k |\mathbb{E} \{ \mathbf{w}_k^H \mathbf{h}_k \}|^2}{\sum_{l=1}^K \rho_l \mathbb{E} \{ |\mathbf{w}_l^H \mathbf{h}_k|^2 \} - \rho_k |\mathbb{E} \{ \mathbf{w}_k^H \mathbf{h}_k \}|^2 + \sigma_{\text{dl}}^2} \quad (54)$$

where the expectations are with respect to all sources of randomness. This lower bound can be used for any choice of precoding. The hardening bound is tight when the level of channel hardening is high.

In this chapter, the preliminaries of the uplink and downlink data transmissions were presented. In the included papers of this thesis, we utilized the UaTF and hardening bounds to derive some of the closed-form expressions for the considered scenarios. These formulas provide some insights into the performance of the investigated cases. Moreover, they were used to devise signal processing algorithms to improve the performance.

Chapter 4

Dual-Polarized Channels

In wireless communications, information is carried by modulated electromagnetic waves. Electromagnetic waves are transverse, meaning that electric and magnetic fields that oscillate in the same plane are perpendicular to each other and the direction of travel. Polarization defines the geometric orientation of the electric field's oscillation direction. For example, a wave is said to be linearly polarized if its electric field changes in such a way that its direction remains parallel to a line in space as the wave propagates. A linearly polarized wave is horizontally/vertically polarized if the polarization is along with the horizontal/vertical axis. Moreover, an electric field (and thus the magnetic field) changing its direction following a clockwise or counter-clockwise circular rotation creates a circularly polarized wave. Similarly, if the electric field variation occurs in an ellipse, it is called an elliptically polarized wave. The linear and circular polarizations are illustrated in Figure 1 and Figure 2, respectively, where $\mathbf{B}$ denotes the magnetic field and $\mathbf{E}$ is the electric field.

Natural light itself is unpolarized meaning that the direction of electric field varies randomly. A wave with desired polarization can be generated from an unpolarized wave using phase retarders and polarizers [57]. It is important to notice that for any type of polarization, there is a corresponding orthogonal polarization. For instance, vertical and horizontal linearly polarized waves are mutually orthogonal, such that their electric fields oscillate at right angles to each other. Another example of orthogonal linearly polarized waves is slant waves that are polarized at -45° and $+45^\circ$ with respect to the reference plane. For circularly/elliptically polarized waves, the clockwise (CW) and counter-clockwise (CCW) rotation correspond to mutually orthogonal states. The orthogonality of wave polarizations can be utilized in wireless communications as an additional degree of freedom to carry information.

Figure 1: Linearly Polarized Wave.

Figure 2: Circularly Polarized Wave.

Mathematically, in Cartesian coordinates, the complex amplitude of a wave traveling along with positive $\hat{\mathbf{z}}$ -direction can be expressed as [57]

$$\mathbf{E} = E_x \hat{\mathbf{x}} + E_y \hat{\mathbf{y}} \quad (55)$$

where the electric fields in x -axis and y -axis are E_x and E_y , respectively. The electric fields are complex numbers and can be written as

$$E_x = |E_x| e^{j\theta_x}, \quad (56)$$

$$E_y = |E_y| e^{j\theta_y}. \quad (57)$$

It is common and useful to represent the wave's polarization state by a normalized Jones vector containing these two complex amplitudes as

$$\mathbf{J} = \frac{1}{\sqrt{|E_x|^2 + |E_y|^2}} \begin{bmatrix} |E_x| e^{j\theta_x} \\ |E_y| e^{j\theta_y} \end{bmatrix}. \quad (58)$$

According to Jones vector notation, most frequently used polarization states are defined as

$$\text{Horizontal: } \mathbf{J}_H = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad \text{Vertical: } \mathbf{J}_V = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \quad (59)$$

$$\text{Slant } +45^\circ: \mathbf{J}_{+45} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \text{Slant } -45^\circ: \mathbf{J}_{-45} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad (60)$$

$$\text{CW circular: } \mathbf{J}_{CW} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -j \end{bmatrix} \quad \text{CCW circular: } \mathbf{J}_{CCW} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ j \end{bmatrix}. \quad (61)$$

4.1 Antenna Polarization

The polarization of an antenna is defined by the polarization of radiated and responded signals [58]. If an incident wave has a different polarization from the antenna, all of the energy in the wave will not be captured. A portion of the power will be lost due to polarization mismatch. In the extreme case, if it happens that the received signal and antenna have orthogonal polarization states, no power will be received at all (in free space). One potential source of the polarization mismatches is that mobile devices are arbitrarily rotated by the users. In addition to polarization mismatches, one specific polarization state can experience severe fading dips in some channel conditions. To mitigate these effects and utilize both of the orthogonal dimensions, dual-polarized antennas are used in radio access networks [59].

An antenna polarization state can be represented by an unit-norm vector [60, 61]. Assuming arbitrary linear polarization, we can write a unit-norm Jones vector

$$\mathbf{p} = \begin{bmatrix} \cos(\theta) \\ \sin(\theta) \end{bmatrix} = \frac{1}{\sqrt{1 + \tan^2(\theta)}} \begin{bmatrix} 1 \\ \tan(\theta) \end{bmatrix} \quad (62)$$

where $\theta = 0$ gives horizontal polarization $\begin{bmatrix} 1 \\ 0 \end{bmatrix}$ and $\theta = \frac{\pi}{2}$ gives corresponds to vertical polarization $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$. The circular and elliptical polarization states can be characterized similarly. However, we focus on linearly polarized antennas since typical propagation environments interact more favorably with linearly polarized waves [62].

To illustrate the importance of polarization match, consider a simplified scenario where both the receiver and transmitter sides are equipped with a single antenna. The polarizations of the receiver and transmitter antennas are described by $\mathbf{p}_r = \frac{1}{\sqrt{1 + \tan^2(\theta_r)}} \begin{bmatrix} 1 \\ \tan(\theta_r) \end{bmatrix}$ and $\mathbf{p}_t = \frac{1}{\sqrt{1 + \tan^2(\theta_t)}} \begin{bmatrix} 1 \\ \tan(\theta_t) \end{bmatrix}$, respectively. For the sake of argument, the channel is LoS and the pathloss between the receiver and transmitter is taken as $\beta = 1$. Then, the channel value that is proportional to the received voltage on the receiving port becomes [61, 63]

$$h_{11} = \mathbf{p}_r^T \mathbf{p}_t = \frac{1 + \tan(\theta_t) \tan(\theta_r)}{\sqrt{1 + \tan^2(\theta_r)} \sqrt{1 + \tan^2(\theta_t)}} = \cos(\theta_r - \theta_t). \quad (63)$$

From (63), we observe that if the transmit and receive antenna polarizations match ($\theta_r = \theta_t$) then there is no power loss since $h_{11} = 1$. On the other hand, when the antennas have orthogonal polarizations ($\theta_r = \theta_t \pm \frac{\pi}{2}$) no signal can be recovered, $h_{11} = 0$. To investigate the distribution of levels of received powers with random antenna orientations at both sides, we plot $|\cos(\theta_r - \theta_t)|$ for uniformly distributed ($\theta_r - \theta_t$) between 0 and $\frac{\pi}{2}$ in Figure 3. It is seen that by 10% chance the received power is approximately 16 dB less than the maximum level of 0 dB.

To ensure that we do not lose power from polarization mismatches, dual-polarized antennas can be utilized as an alternative to the uni-polarized antennas. The polarization states of a dual-polarized antenna can be represented by two unit-norm vectors [60, 64]. Therefore, we define the antenna polarization matrix as

$$\bar{\mathbf{F}} = [\mathbf{p}_1, \mathbf{p}_2] \quad (64)$$

where $\mathbf{p}_1 = \frac{1}{\sqrt{1 + \tan^2(\theta_1)}} \begin{bmatrix} 1 \\ \tan(\theta_1) \end{bmatrix}$ and $\mathbf{p}_2 = \frac{1}{\sqrt{1 + \tan^2(\theta_2)}} \begin{bmatrix} 1 \\ \tan(\theta_2) \end{bmatrix}$. Ideally, dual-polarized antennas are composed of two orthogonally polarized antenna ports in

Figure 3: The cumulative distribution of $\cos(\theta_r - \theta_t)$ for $(\theta_r - \theta_t) \in \mathcal{U}[0, \frac{\pi}{2}]$ [61].

order to minimize the self-interference i.e., $\theta_2 = \theta_1 + \frac{\pi}{2}$. In this case, we have

$$\bar{\mathbf{F}} = \frac{1}{\sqrt{1 + \tan^2(\theta_1)}} \begin{bmatrix} 1 & -\tan(\theta_1) \\ \tan(\theta_1) & 1 \end{bmatrix}. \quad (65)$$

On the other hand, for imperfectly designed and manufactured antennas, $\mathbf{p}_1$ and $\mathbf{p}_2$ may not be orthogonal. In this case, the non-orthogonality causes a polarization coupling between the antenna ports. Due to the reduced array gain from a common phase center, the polarization matrix is scaled as [60]

$$\mathbf{F} = \frac{1}{\sqrt{1 + \mathbf{p}_1^T \mathbf{p}_2}} [\mathbf{p}_1, \mathbf{p}_2]. \quad (66)$$

Notice that if there is no parallelity i.e., $\mathbf{p}_1^T \mathbf{p}_2 = 0$, the scaling coefficient is equal to unity. In the extreme case of total alignment ($\mathbf{p}_1^T \mathbf{p}_2 = 1$), there is effectively only one single polarization direction and the transmitted/received signal power will be halved.

To investigate the benefit of dual-polarized antennas, we now replace the uni-polarized receiver antenna with a dual-polarized antenna in the previous scenario. The dual-polarized antenna has the antenna polarization matrix

$$\mathbf{F}_r = \frac{1}{\sqrt{1 + \mathbf{p}_{r1}^T \mathbf{p}_{r2}}} [\mathbf{p}_{r1}, \mathbf{p}_{r2}], \quad (67)$$

and the transmitted signal from the single antenna uni-polarized transmitter has the polarization vector $\mathbf{p}_t = \frac{1}{\sqrt{1+\tan^2(\theta_t)}} \begin{bmatrix} 1 \\ \tan(\theta_t) \end{bmatrix}$. Then, the channel coefficients become

$$\begin{aligned} \mathbf{H}_{2 \times 1} &= \begin{bmatrix} h_{11} \\ h_{21} \end{bmatrix} = \frac{1}{\sqrt{1 + \mathbf{p}_{r1}^T \mathbf{p}_{r2}}} [\mathbf{p}_{r1}, \mathbf{p}_{r2}]^T \mathbf{p}_t \\ &= \frac{1}{\sqrt{1 + \cos(\theta_{r1} - \theta_{r2})}} \begin{bmatrix} \cos(\theta_{r1} - \theta_t) \\ \cos(\theta_{r2} - \theta_t) \end{bmatrix}. \end{aligned} \quad (68)$$

Applying maximum ratio combining at the receiver side gives

$$\|\mathbf{H}_{2 \times 1}\|^2 = \frac{\cos(\theta_{r1} - \theta_t)^2 + \cos(\theta_{r2} - \theta_t)^2}{1 + \cos(\theta_{r1} - \theta_{r2})}. \quad (69)$$

Based on (69), we observe that if the dual-polarized antenna ports have polarization states $\theta_{r2} = \theta_{r1} + \frac{\pi}{2}$, the numerator becomes $\cos(\theta_{r1} - \theta_t)^2 + \sin(\theta_{r1} - \theta_t)^2 = 1$ and $\cos(\theta_{r1} - \theta_{r2}) = 0$. Thus, there is no power loss, no matter what polarization orientation the transmitter has. Contrarily, in the worst case, if the receiver antenna ports have the same polarization such that $\theta_{r2} = \theta_{r1}$, the gain (69) reduces to the case with single uni-polarized antenna as in the previous scenario where the channel gain was $\cos(\theta_{r1} - \theta_t)^2$.

Next, we also consider a case where both the receiver and transmitter are equipped with dual-polarized antennas with polarization matrices $\mathbf{F}_r$ and $\mathbf{F}_t$, respectively. In this scenario, polarization coupling can occur at both sides. The channel coefficients become

$$\begin{aligned} \mathbf{H}_{2 \times 2} &= \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} = \mathbf{F}_r^T \mathbf{F}_t = \frac{1}{\sqrt{1 + \mathbf{p}_{r1}^T \mathbf{p}_{r2}}} \frac{1}{\sqrt{1 + \mathbf{p}_{t1}^T \mathbf{p}_{t2}}} [\mathbf{p}_{r1}, \mathbf{p}_{r2}]^T [\mathbf{p}_{t1}, \mathbf{p}_{t2}] \\ &= \frac{1}{\sqrt{1 + \cos(\theta_{r1} - \theta_{r2})}} \frac{1}{\sqrt{1 + \cos(\theta_{t1} - \theta_{t2})}} \begin{bmatrix} \cos(\theta_{r1} - \theta_{t1}) & \cos(\theta_{r1} - \theta_{t2}) \\ \cos(\theta_{r2} - \theta_{t1}) & \cos(\theta_{r2} - \theta_{t2}) \end{bmatrix}. \end{aligned} \quad (70)$$

In this scenario, when both the transmitter and receiver dual-polarized antennas are free from polarization misalignment such that $\theta_{r2} = \theta_{r1} + \frac{\pi}{2}$ and $\theta_{t2} = \theta_{t1} + \frac{\pi}{2}$, the received signals can be easily obtained by applying maximum ratio combining matrix $\mathbf{V} = \mathbf{H}_{2 \times 2}^T$ [61]. Therefore, the diagonal elements are

$$[\mathbf{VH}_{2 \times 2}]_{11} = \cos^2(\theta_{r1} - \theta_{t1}) + \cos^2(\theta_{r2} - \theta_{t1}), \quad (71)$$

$$[\mathbf{VH}_{2 \times 2}]_{22} = \cos^2(\theta_{r2} - \theta_{t2}) + \cos^2(\theta_{r1} - \theta_{t2}), \quad (72)$$

and the off-diagonal elements are

$$[\mathbf{VH}_{2 \times 2}]_{12} = [\mathbf{VH}_{2 \times 2}]_{21} = \cos(\theta_{r1} - \theta_{t1}) \cos(\theta_{r1} - \theta_{t2}) + \cos(\theta_{r2} - \theta_{t1}) \cos(\theta_{r2} - \theta_{t2}). \quad (73)$$

Notice that $\cos(\theta_{r2} - \theta_{t1}) = \cos(\theta_{r1} - \theta_{t1} + \frac{\pi}{2}) = -\sin(\theta_{r1} - \theta_{t1})$, $\cos(\theta_{r1} - \theta_{t2}) = \cos(\theta_{r2} - \theta_{t2} - \frac{\pi}{2}) = \sin(\theta_{r2} - \theta_{t2})$ and $\cos(\theta_{r2} - \theta_{t2}) = \cos(\theta_{r1} - \theta_{t1})$. Substituting these gives the diagonal and off-diagonal elements as

$$[\mathbf{VH}_{2 \times 2}]_{11} = \cos^2(\theta_{r1} - \theta_{t1}) + \sin^2(\theta_{r1} - \theta_{t1}) = 1, \quad (74)$$

$$[\mathbf{VH}_{2 \times 2}]_{22} = \cos^2(\theta_{r2} - \theta_{t2}) + \sin^2(\theta_{r2} - \theta_{t2}) = 1, \quad (75)$$

$$[\mathbf{VH}_{2 \times 2}]_{12} = [\mathbf{VH}_{2 \times 2}]_{21} = 0. \quad (76)$$

Thus, in the ideal case, we observe that when both of the dual-polarized antennas are separated by 90° the maximum ratio combining algorithm is able to decouple the received data streams. Note that even in a scenario where the receiver and transmitter sides have mixed polarizations, e.g., one of them is slant polarized while the other one is vertical/horizontal polarized, there is no power loss. On the other hand, if the antennas are not ideal, then we will encounter self-interference that causes a power loss. In this case, zero-forcing combining can be applied to separate the received data streams [61].

The antennas can be designed well with minimal hardware impairments such that the polarization misalignment effects are minimized. The cross-polar isolation (XPI) is a quality metric of antennas and it is defined as the ratio of the desired co-polar and undesired cross-polar power levels radiated/received from an antenna [61]. The XPI values are infinite for perfectly isolated antennas. In wireless communications, XPI levels more than 25 dB is a common specification for good-quality antennas [63, Chapter 7]. If the antenna ports reuse the same frequency, it is preferred to have XPIs around 30 dB. So far, we only considered the non-fading case. A more complex and prominent depolarization mechanism comes from the fading channels and it is described in the following section.

4.2 Channel Depolarization

In free-space, cross-polar transmissions (e.g., from a vertical polarized BS antenna to horizontal polarized UE antenna) is zero under ideal conditions as discussed in the previous section. However, in practice, the performance of dual-polarized systems strongly depends on propagation characteristics. The propagation environment causes cross-polarization scattering that changes the initial polarization state of the electromagnetic waves on the way from the transmitter to the receiver. Therefore, the resulting polarization deviates from that of the transmitted wave. According to [62],

the deviation from the original polarization state is smallest if the wave had been transmitted with vertical or horizontal polarizations. It is argued that this is most likely because the ground and most human-made surfaces are either horizontal or vertical.

In [65], two distinct behaviors of dual-polarized channels are identified whereas a practical scenario may lie somewhere in between them.

- In **poor scattering** environments: the levels of channel depolarization (also called cross-polarization coupling/scattering) are low. It means that a wave is more likely to maintain its initial polarization state with small deviations during propagation due to the lack of scatterers. Therefore, the cross-polarized waves can be separated easily at the receiver side. In this case, the two orthogonal polarization states can be used for multiplexing signals.
- In **rich scattering** environments: the amounts of cross-polarization coupling are high. It means that interactions with the objects in the environment cause variations in the polarization. At the same time, it is observed that the correlation between the two cross-polarized signals is low. In this case, the advantage of low correlation between the polarization states can be utilized.

The channel with single dual-polarized antennas at both the transmitter and receiver sides can be written as

$$\mathbf{H} = \begin{bmatrix} h_{VV} & h_{VH} \\ h_{HV} & h_{HH} \end{bmatrix} \quad (77)$$

where the first/second subscript denotes the receiver/transmitter antenna component. The letter V corresponds to vertical polarization whereas H shows the horizontal polarization. Thus, the channel coefficients represent the input-output relations between V to V, V to H, H to V and H to H polarizations. The analysis holds for any set of two orthogonal orthogonal polarization directions. We just refer to them as V and H polarized for notational convenience. Quantitatively, the channel cross-polarization discrimination (XPD) is the measure of the channel's ability to maintain radiated or received polarization purity between the orthogonally polarized signals. In [65, 66], the XPDs between the cross and co-polar components are defined based

on the instantaneous channel gains as

$$\text{XPD}_V^{\text{Rx}} = \frac{|h_{\text{VV}}|^2}{|h_{\text{VH}}|^2}, \quad (78)$$

$$\text{XPD}_H^{\text{Rx}} = \frac{|h_{\text{HH}}|^2}{|h_{\text{HV}}|^2}, \quad (79)$$

$$\text{XPD}_V^{\text{Tx}} = \frac{|h_{\text{VV}}|^2}{|h_{\text{HV}}|^2}, \quad (80)$$

$$\text{XPD}_H^{\text{Tx}} = \frac{|h_{\text{HH}}|^2}{|h_{\text{VH}}|^2}, \quad (81)$$

$$\text{XPD} = \frac{|h_{\text{VV}}|^2 + |h_{\text{HH}}|^2}{|h_{\text{VH}}|^2 + |h_{\text{HV}}|^2} \quad (82)$$

where Rx and Tx correspond to the receiver and transmitter, respectively. The superscript Rx/Tx denotes that the polarization of the referred side is fixed. The last equation (82) is the overall XPD. In [60], symmetric leakage between the V/H polarizations is assumed. The XPD is defined based on averaged channel gains as

$$\text{XPD} = \frac{\mathbb{E}\{|h_{\text{VV}}|^2\}}{\mathbb{E}\{|h_{\text{HV}}|^2\}} = \frac{\mathbb{E}\{|h_{\text{HH}}|^2\}}{\mathbb{E}\{|h_{\text{VH}}|^2\}} \quad (83)$$

where the symmetry assumption is motivated by the measurement results in [62]. The authors conducted a series of experiments both in outdoor and indoor environment and reached the following conclusions. First, V and H polarized waves experience the same path loss on average. The co-polar channel components $\mathbb{E}\{|h_{\text{VV}}|^2\}$ and $\mathbb{E}\{|h_{\text{HH}}|^2\}$ have the same powers whereas the cross-polarized components $\mathbb{E}\{|h_{\text{VH}}|^2\}$ and $\mathbb{E}\{|h_{\text{HV}}|^2\}$ have also the same power levels that are suppressed by 5 – 15 dB compared to the co-polarized ones. Besides, the polarization leakage increases with increasing pathloss. Second, the co- and cross-polar power levels change much slower than the fast-fading variations. Third, in a typical cellular environment, no fast-fading correlation between the V/H polarized signals is observed. A collection of other experimental studies can be found in [66, Table I].

Chapter 5

Intelligent Reflecting Surfaces

In the years to come, it is expected that global mobile data traffic will increase 55 percent each year [67]. Furthermore, not only the higher data rate requirements but also energy efficiency, global coverage, low latency, and heterogeneity issues pose critical challenges [68]. To be able to meet the ambitious requirements of future networks and achieve sustainable capacity growth, the search for beyond 5G technologies has already started while 5G networks are currently being rolled out.

Potentially, a physical layer technology can play a critical role as a disruptive innovation since the main limitations of wireless networks come from the laws of physics. In mobile communications, intelligent reflecting surface (IRS), also called under names software-controlled metasurfaces [69, 70], reconfigurable intelligent surfaces [71], is considered as a candidate for such technology. An IRS, consisting of reconfigurable metamaterials, can be used to partially control the radio environment and thereby bring new features to wireless communications.

5.1 What is an IRS?

An IRS is a thin two-dimensional metamaterial (i.e., engineered material) that can control and transform electromagnetic waves [72, 73]. It has been demonstrated experimentally that metasurfaces can dynamically produce unusual scattering, polarization, and focusing properties to obtain desired radiation patterns [74, 75]. Thanks to rapid recent development in lumped elements such as micro-electro-mechanical-systems (MEMS), varactors and PIN diodes, and tunable materials such as liquid crystals and graphene, metasurfaces with flexible functionalities can be successfully realized with low implementation cost and light weight [76]. This has opened up exciting opportunities to use metasurfaces to solve problems in wireless communication research. Metasurfaces are implemented as an array of discrete scattering elements. Each element (also known as a meta-atom or lattice) has the ability to

introduce a phase shift to an incident wave. The change in the local surface phase is achieved by tuning the surface impedance which enables manipulation of the impinging wave.

5.2 Basics of System Modeling with IRS

Consider a basic communication system where a single-antenna transmitter sends signals to a single-antenna receiver. The transmitter sends an unmodulated passband signal $s(t) = \text{Re} \{e^{j2\pi f_c t}\}$ where f_c is the carrier frequency. The signal reaches the receiver via a direct path and an uncontrollable path due to a scatterer as illustrated in Figure 1. Each path introduces a time delay and an amplitude attenuation. Then, the passband signal at the receiver is

$$s_r(t) = \sqrt{\rho_1} \cos(2\pi f_c(t - \tau_1)) + \sqrt{\rho_2} \cos(2\pi f_c(t - \tau_2)) \quad (84)$$

where the time delays corresponding to the direct and uncontrolled path are $\tau_1 = \frac{d_1}{c}$ and $\tau_2 = \frac{d_2}{c}$, respectively. The associated path lengths are d_1 and d_2 and c is the speed of light. In (84), we see the summation of two sinusoidal signals with different amplitudes and phases. Depending on the time delays τ_1 and τ_2 , the terms are added constructively and destructively. For example, if the waves are out-of phase such that $\tau_2 = \tau_1 \pm 0.5/f_c$ they will cancel each other completely for $\rho_1 = \rho_2$. On the other hand, in-phase waves with delays $\tau_2 = \tau_1 \pm 1/f_c$ will be added constructively. Notice that f_c is typically a large number, around several GHz. Therefore, even minor time delay differences lead to drastic changes in the received signal power.

Figure 1: Illustration of a two path propagation model.

To make sure that the receiver always gets a coherent combining of the signals, a controllable scatterer can be introduced to the system. This device has ability to add a phase-shift ϕ to the signal. Then, the received signal becomes

$$s_r(t) = \sqrt{\rho_1} \cos(2\pi f_c(t - \tau_1)) + \sqrt{\rho_2} \cos(2\pi f_c(t - \tau_2) - \phi). \quad (85)$$

In this case, selecting the controllable phase as $\phi = 2\pi f_c(\tau_2 - \tau_1)$ ensures the constructive addition of the sinusoids.

Figure 2: IRS-aided communication system.

Obviously, typical wireless channels have more complicated characteristics than the two path propagation example above. Yet, the idea of partially controlling the time delays can be adapted by utilizing an IRS. To solely focus on IRS, consider a single-antenna transmitter and receiver again. An IRS with N reconfigurable elements is deployed between the transmitter and receiver as illustrated in Figure 2. The colors of each square on IRS represent a corresponding phase-shift. The transmitter sends $s(t) = \text{Re} \{x(t)e^{j2\pi f_c t}\}$ where $x(t)$ is a narrowband baseband signal with the bandwidth $B/2$ Hz such that $B \ll f_c$. Then, the received passband signal over the element $n \in \{1, \dots, N\}$ of the IRS is

$$s_{r,n}(t) = \text{Re} \left\{ \left[\sqrt{\alpha_n \gamma \beta_n} e^{-j2\pi f_c \tau_{n,a}} e^{-j2\pi f_c \tau_{\phi_n}} e^{-j2\pi f_c \tau_{n,b}} x(t) \right] e^{j2\pi f_c t} \right\} \quad (86)$$

where propagation losses α_n, β_n and time delays $\tau_{n,a}, \tau_{n,b}$ are induced by the transmitter-to-IRS and IRS-to-receiver channels, respectively. The amplitude attenuation $\gamma \in [0, 1]$ and the controlled time delay τ_{ϕ_n} are added by the IRS. The channel attenuations and time delays are determined by distance related pathloss, shadowing and multipath fading. Ignoring any hardware impairment such as coupling at the IRS, the corresponding baseband signal model over all the N IRS elements is

$$s_r(t) = \sum_{n=1}^N \sqrt{\alpha_n \gamma \beta_n} e^{-j2\pi f_c \tau_{n,a}} e^{-j2\pi f_c \tau_{\phi_n}} e^{-j2\pi f_c \tau_{n,b}} x(t). \quad (87)$$

Similarly, the baseband signal received via the direct path can be written as

$$s_d(t) = \sqrt{\rho}e^{-j2\pi f_c \tau_d}x(t) \quad (88)$$

where ρ is the propagation loss and τ_d is the time delay associated with the direct path. Then, the received signal is

$$y(t) = \sqrt{\rho}e^{-j2\pi f_c \tau_d}x(t) + \sum_{n=1}^N \sqrt{\alpha_n \gamma \beta_n} e^{-j2\pi f_c \tau_{n,a}} e^{-j2\pi f_c \tau_{\phi_n}} e^{-j2\pi f_c \tau_{n,b}} x(t) + n \quad (89)$$

where $n \sim \mathcal{CN}(0, \sigma^2)$ is the receiver noise. The transmit power is $\mathbb{E}\{|x(t)|^2\} = P$. We can write the SNR as

$$\begin{aligned} & \frac{P}{\sigma^2} \left| \sqrt{\rho}e^{-j2\pi f_c \tau_d} + \sum_{n=1}^N \sqrt{\alpha_n \gamma \beta_n} e^{-j2\pi f_c \tau_{n,a}} e^{-j2\pi f_c \tau_{\phi_n}} e^{-j2\pi f_c \tau_{n,b}} \right|^2 \\ & \leq \frac{P}{\sigma^2} \left| \sqrt{\rho}e^{-j2\pi f_c \tau_d} + \sum_{n=1}^N \sqrt{\alpha_n \gamma \beta_n} e^{-j2\pi f_c \tau_d} \right|^2 \\ & = \frac{P}{\sigma^2} \left| \sqrt{\rho} + \sum_{n=1}^N \sqrt{\alpha_n \gamma \beta_n} \right|^2 \end{aligned} \quad (90)$$

where the upper bound is obtained by the Cauchy-Schwartz inequality. The upper bound is achieved if the delays at the IRS are selected as $\tau_{\phi_n} = \tau_d - \tau_{n,a} - \tau_{n,b}$ for $n \in \{1, \dots, N\}$. As the number of IRS elements, users and antennas increase the complexity of the communication system increases as expected.

In this thesis, we only consider frequency-flat channels. Practical systems may operate over frequency-selective channels. In such cases, more complicated orthogonal frequency-division multiplexing (OFDM) based methods would be applied [77, 78].

5.3 Prospective Use Cases

An immense amount of time and resources are required to bring a new technology concept, such as IRS, from theory to practice. Very convincing benefits compared to existing technologies must be established to motivate such an investment. Commonly envisioned use cases of IRS-aided communications are coverage extension, rank improvement, and interference suppression [79].

The research efforts are mainly focused on the optimization of IRS configurations for coverage extension scenarios. IRS can be particularly effective when the direct path is weak due to some blockage. However, conventional relays already provide a competitive performance and IRS must prove its advantages [80]. In addition, using the IRS for improved spatial multiplexing and interference mitigation is a

promising research direction. In this use case, cell-free massive MIMO is also an emerging competitive technology. Frequently mentioned promising advantages of IRS are low hardware cost, energy efficiency due to lack of radio frequency chains, being able to operate on full-duplex mode [81]. Some industrial efforts are already resulted in prototypes [79, Table I]. Therefore, performance evaluations in the following years will prove whether IRS is a viable and competitive technology in these use cases or not. Furthermore, the channel rank improvement ability of an IRS-aided systems is discussed in Paper E and [82]. One of the classical bottlenecks of point-to-point MIMO communications is that the capacity gains provided by spatial multiplexing are only large at high SNR, and high SNR channels are mainly appearing in LoS scenarios where the channel matrix has low rank and therefore does not support spatial multiplexing. In this case, IRSs can be deployed to create additional multipaths to the increase channel rank.

Along with these mainstream research directions, the role of IRS is studied in the following topics: sensing and localization [83, 84], IRS-aided THz communications [85, 86], wireless power transfer [87, 88], physical layer security [89, 90], mobile edge computing [91, 92], unmanned aerial vehicle communications [93, 94].

Chapter 6

Deep Learning for Wireless Communications

The new generations of wireless communications are more likely to employ multiple technologies jointly, each with its specific requirements. For example, it is envisioned that 5G and the consecutive generations will support Internet of Things, Ultra-Reliable Low Latency Communications, enhanced Mobile Broadband and Unmanned Aerial Vehicles applications [95]. Along with the heterogeneity, the number of connected devices and their demand for higher data rates increase every year. These critical challenges introduce higher levels of complexity than the previous generations.

Traditionally, mathematical models are utilized to design and operate wireless networks. Inherently, there is always a trade-off between tractability and accuracy when the mathematical models are considered. Some complex mathematical models can be prohibitive for real-time usage. The wireless networks are desired to be intelligent enough to adapt flexibly to varying network conditions to provide seamless connectivity. This led to a growing interest in data-driven approaches as a complement to traditional methods. In recent years, the data-driven approaches have recently become viable due to expanded computing capabilities and the availability of large datasets from growing data traffic.

By utilizing deep learning methods based on artificial neural networks, it can be possible to learn from previous data and based on this experience improve actions for the future. The learning algorithms can be categorized into unsupervised, supervised and reinforcement learning:

- **Unsupervised Learning:** the algorithm must discover the underlying pattern in the input data to carry out the desired task without any guidance.
- **Supervised Learning:** the goal is to find the mapping/formula between the

input and the corresponding output. The outputs are referred to as labels or targets.

- **Reinforcement Learning:** the algorithm interacts with the surrounding environment through a feedback loop between the algorithm and the environment. Accordingly, it adapts itself to the changes over time.

In Paper F, we used the supervised learning approach since the goal was to find the mapping between the received pilot signals and the IRS configurations.

Artificial neural networks are the enablers of deep learning algorithms. They consist of layers of processing units referred to as neurons. The layers are called input, hidden, or output layers depending on their roles. The input layer is responsible for obtaining the input data and forwarding it to the rest of the network. The hidden layers process the data and the output layer applies the final processing and gives the output. The weight and bias terms model the importance of connections among the neurons. Based on how the information travels from the input layer to the output layer, the artificial neural networks are mainly categorized as feedforward neural networks and recurrent neural networks. In a feedforward neural network, processed data only flows from the input layer to the output layer, whereas feedback loops are allowed in the recurrent neural networks.

6.1 Preliminaries of Feedforward Neural Networks

In this section, we consider a feedforward neural network with L fully-connected layers as illustrated in Figure 1. In the fully-connected layers, each neuron is connected to all neurons in the previous layer and the following layer. The input vector $\mathbf{r}_0 \in \mathbb{R}^{N_0}$ is fed to the network by N_0 input neurons. It is processed through the hidden layers with Layer l having N_l neurons. The output layer with N_L neurons gives the output vector $\mathbf{r}_L \in \mathbb{R}^{N_L}$. A feedforward neural network is described by the mapping $f(\mathbf{r}_0; \boldsymbol{\theta}) : \mathbb{R}^{N_0} \rightarrow \mathbb{R}^{N_L}$ through L steps as [96, 97]

$$f_l(\mathbf{r}_{l-1}; \boldsymbol{\theta}_l) = \sigma_l(\mathbf{W}_l \mathbf{r}_{l-1} + \mathbf{b}_l), \quad l \in 1, \dots, L \quad (91)$$

where $f_l(\mathbf{r}_{l-1}; \boldsymbol{\theta}_l) : \mathbb{R}^{N_{l-1}} \rightarrow \mathbb{R}^{N_l}$ is the mapping of the layer l . The set of parameters is $\boldsymbol{\theta}_l = \{\mathbf{W}_l, \mathbf{b}_l\}$ where $\mathbf{W}_l \in \mathbb{R}^{N_l \times N_{l-1}}$ and $\mathbf{b}_l \in \mathbb{R}^{N_l}$ denote the weight matrix and bias vector, respectively. Also, the element-wise nonlinear function $\sigma_l(\cdot) : \mathbb{R}^{N_l} \rightarrow \mathbb{R}^{N_l}$ is referred to as the activation function. The equation (91) describes a two-step process. First, $\mathbf{r}_{l-1}$ is taken from the previous layer and the affine transformation $\mathbf{W}_l \mathbf{r}_{l-1} + \mathbf{b}_l$ is applied. Then, applying the activation function $\sigma_l(\cdot)$ gives the vector $\mathbf{r}_l$.

Figure 1: A feedforward neural network.

Some commonly used activation functions are sigmoid, tanh, rectified linear unit (ReLU) and exponential linear unit (ELU). The activation function is applied to each element of its input vector. The sigmoid activation function is defined as

$$\text{sigmoid}(r_{n,l}) = \frac{1}{1 + e^{-r_{n,l}}} \quad (92)$$

and the hyperbolic tangent function is

$$\tanh(r_{n,l}) = \frac{e^{r_{n,l}} - e^{-r_{n,l}}}{e^{r_{n,l}} + e^{-r_{n,l}}}. \quad (93)$$

The sigmoid function ranges between zero and one, whereas the tanh function has the range from minus one to plus one. The sigmoid and tanh functions are related as $\tanh(r_{n,l}) = 2\text{sigmoid}(r_{n,l}) - 1$. The sigmoid function is typically used in probability estimation applications because of its range. In recent times, both the sigmoid and tanh functions are less frequently used due to a problem called vanishing gradients that slows down the convergence. It occurs since the input space is limited between zero and one that results in derivatives very close to zero for a large portion of the domain. The widely-used activation function ReLU is defined as

$$\text{ReLU}(r_{n,l}) = \max(0, r_{n,l}). \quad (94)$$

This function is linear for positive values, and it makes ReLU easier to be optimized with gradient based methods. ELU is identical to ReLU for positive input values. For negative values, it is defined as

$$\text{ELU}(r_{n,l}) = \alpha(e^{r_{n,l}} - 1) \quad (95)$$

where α is typically set to 1. There are numerous other activation functions with different mathematical properties and performances.

The universal approximation theorem states that a fully-connected feedforward neural network is capable of approximating any deterministic continuous function over a compact set arbitrarily well with enough neurons and activation functions [98]. However, the theorem does not specify the number of neurons and layers, and how to configure the parameters.

The neural network is said to be trained when the weight and bias parameters are tuned for learning the desired input-output relation. Generally, a set of input and labeled training data pairs $(\mathbf{r}_{0,i}, \mathbf{r}_{L,i}^*), i = 1, \dots, P$ are used for the training process where $\mathbf{r}_{L,i}^*$ is the desired output and $\mathbf{r}_{0,i}$ is the input data. The aim is to minimize the loss function

$$L(\boldsymbol{\theta}) = \frac{1}{P} \sum_{i=1}^P l(\mathbf{r}_{L,i}^*, \mathbf{r}_{L,i}) \quad (96)$$

where $l(\cdot)$ is a loss function that models the error between the actual output $\mathbf{r}_{L,i}$ when $\mathbf{r}_{0,i}$ is used as the input and the desired output $\mathbf{r}_{L,i}^*$. Some widely used loss functions are the mean squared error (MSE) and cross-entropy, given respectively by [99]

$$l(\mathbf{u}, \mathbf{v}) = \text{MSE}(\mathbf{u}, \mathbf{v}) = \sum_{n=1}^N (\mathbf{u}_n - \mathbf{v}_n)^2 \quad (97)$$

$$l(\mathbf{u}, \mathbf{v}) = H(\mathbf{u}, \mathbf{v}) = - \sum_{n=1}^N \mathbf{u}_n \log(\mathbf{v}_n) + (1 - \mathbf{u}_n) \log(1 - \mathbf{v}_n) \quad (98)$$

where $\mathbf{u}, \mathbf{v} \in \mathbb{R}^N$. Then, the problem is to find the parameters that minimize the loss in (96). Various algorithms for finding good $\boldsymbol{\theta}$ values are given in [100, Chapter 8].

6.2 Applications to Wireless Communications

Advancements in computational capabilities and deep learning algorithms led to an increasing research interest in wireless communications applications as in many other fields. The efforts are mainly focused on either simplification of tasks such as channel estimation, encoding, decoding, localization or resource allocation with reduced complexity [99, 101].

A pioneering work that falls in the first category is [96]. The authors introduce an architecture called autoencoder that emulates the transmitter and receiver implementations of a point-to-point wireless communication system using deep feedforward neural networks. The autoencoder scheme outperformed the traditional baselines in terms of block error rates. In addition, the problem of channel estimation with

low complexity is studied in [102]. It is shown that a deep neural network can successfully learn the MMSE channel estimator. The line of works that studies the resource allocation with reduced complexity can be found in [103, 104].

Similar to other wireless communications fields, deep learning is also applied to the IRS-aided communications [105]. IRSs typically have a large number of elements that may create a huge training overhead to implement the configuration that is described in Chapter 5. Besides, the elements are purposely designed to not have any active components, therefore, they are not able to process any pilot signal. In Paper F, we proposed a deep learning approach for phase reconfiguration at an IRS in order to learn and make use of the local propagation environment. The proposed method uses the received pilot signals reflected through the IRS to train the deep feedforward network.

Bibliography

- [1] M. Cooper, “The myth of spectrum scarcity,” DYNA llc, Tech. Rep., Mar. 2010.
- [2] H. H. Beverage and H. O. Peterson, “Diversity receiving system of R.C.A. communications, inc., for radiotelegraphy,” *Proceedings of the Institute of Radio Engineers*, vol. 19, no. 4, pp. 529–561, April 1931.
- [3] Cisco, “Visual networking index: Global mobile data traffic forecast update, 2016 – 2021,” Tech. Rep., Feb. 2017.
- [4] T. L. Marzetta, “Noncooperative cellular wireless with unlimited numbers of base station antennas,” *IEEE Transactions on Wireless Communications*, vol. 9, no. 11, pp. 3590–3600, November 2010.
- [5] T. L. Marzetta, E. G. Larsson, H. Yang, and H. Q. Ngo, “Fundamentals of massive MIMO,” *Cambridge University Press*, 2016.
- [6] E. Björnson, J. Hoydis, and L. Sanguinetti, “Massive MIMO networks: Spectral, energy, and hardware efficiency,” *Foundations and Trends® in Signal Processing*, vol. 11, no. 3-4, pp. 154–655, 2017.
- [7] J. Hoydis, S. ten Brink, and M. Debbah, “Massive MIMO in the UL/DL of cellular networks: How many antennas do we need?” *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 2, pp. 160–171, February 2013.
- [8] H. Yang and T. L. Marzetta, “Massive MIMO with max-min power control in line-of-sight propagation environment,” *IEEE Transactions on Communications*, vol. 65, no. 11, pp. 4685–4693, Nov 2017.
- [9] C. Chen, A. P. Guevara, and S. Pollin, “Scaling up distributed massive MIMO: Why and how,” in *2017 51st Asilomar Conference on Signals, Systems, and Computers*, Oct 2017, pp. 271–276.

- [10] C. Chen, S. Blandino, A. Gaber, C. Desset, A. Bourdoux, L. Van der Perre, and S. Pollin, "Distributed massive MIMO: A diversity combining method for TDD reciprocity calibration," in *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*, Dec 2017, pp. 1–7.
- [11] K. T. Truong and R. W. Heath, "The viability of distributed antennas for massive MIMO systems," in *2013 Asilomar Conference on Signals, Systems and Computers*, Nov 2013, pp. 1318–1323.
- [12] H. Q. Ngo, A. Ashikhmin, H. Yang, E. G. Larsson, and T. L. Marzetta, "Cell-free massive MIMO versus small cells," *IEEE Transactions on Wireless Communications*, vol. 16, no. 3, pp. 1834–1850, March 2017.
- [13] E. Nayebi, A. Ashikhmin, T. L. Marzetta, H. Yang, and B. D. Rao, "Precoding and power optimization in cell-free massive MIMO systems," *IEEE Transactions on Wireless Communications*, vol. 16, no. 7, pp. 4445–4459, July 2017.
- [14] G. Interdonato, E. Björnson, H. N. Quoc, P. Frenger, and E. G. Larsson, "Ubiquitous cell-free massive MIMO communications," *EURASIP Journal on Wireless Communications and Networking*, vol. 2019, no. 1, p. 197, Aug 2019.
- [15] J. Zhang, S. Chen, Y. Lin, J. Zheng, B. Ai, and L. Hanzo, "Cell-free massive MIMO: A new next-generation paradigm," *IEEE Access*, vol. 7, pp. 99 878–99 888, 2019.
- [16] D. Gesbert, S. Hanly, H. Huang, S. Shamai Shitz, O. Simeone, and W. Yu, "Multi-cell MIMO cooperative networks: A new look at interference," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 9, pp. 1380–1408, December 2010.
- [17] S. Venkatesan, A. Lozano, and R. Valenzuela, "Network MIMO: Overcoming intercell interference in indoor wireless systems," in *2007 Conference Record of the Forty-First Asilomar Conference on Signals, Systems and Computers*, Nov 2007, pp. 83–87.
- [18] G. J. Foschini, K. Karakayali, and R. A. Valenzuela, "Coordinating multiple antenna cellular networks to achieve enormous spectral efficiency," *IEE Proceedings - Communications*, vol. 153, no. 4, pp. 548–555, August 2006.
- [19] R. Irmer, H. Droste, P. Marsch, M. Grieger, G. Fettweis, S. Brueck, H. Mayer, L. Thiele, and V. Jungnickel, "Coordinated Multipoint: Concepts, perfor-

- mance, and field trial results,” *IEEE Communications Magazine*, vol. 49, no. 2, pp. 102–111, February 2011.
- [20] Ö. T. Demir, E. Björnson, and L. Sanguinetti, “Foundations of user-centric cell-free massive mimo,” *arXiv preprint arXiv:2108.02541*, 2021.
- [21] E. Björnson, R. Zakhour, D. Gesbert, and B. Ottersten, “Cooperative Multi-cell Precoding: Rate region characterization and distributed strategies with instantaneous and statistical CSI,” *IEEE Transactions on Signal Processing*, vol. 58, no. 8, pp. 4298–4310, Aug 2010.
- [22] R. W. Heath Jr. and A. Lozano, “Foundations of MIMO communication,” *Cambridge University Press*, 2018.
- [23] S. Hur, S. Baek, B. Kim, J. Park, A. F. Molisch, K. Haneda, and M. Peter, “28 GHz channel modeling using 3D ray-tracing in urban environments,” in *2015 9th European Conference on Antennas and Propagation (EuCAP)*, April 2015, pp. 1–5.
- [24] B. Guo, Y. Wu, M. Yang, and J. Li, “28 GHz millimeter wave propagation models based on ray-tracing in urban scenario,” in *2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Aug 2015, pp. 2209–2213.
- [25] M. Jacob, S. Priebe, A. Maltsev, A. Lomayev, V. Erceg, and T. Kürner, “A ray tracing based stochastic human blockage model for the IEEE 802.11ad 60 GHz channel model,” in *Proceedings of the 5th European Conference on Antennas and Propagation (EUCAP)*, April 2011, pp. 3084–3088.
- [26] D. Tse and P. Viswanath, “Fundamentals of wireless communication,” *Cambridge University Press*, 2005.
- [27] A. Goldsmith, “Wireless communications,” *Cambridge University Press*, 2005.
- [28] S. Blandino, C. Desset, G. Mangraviti, A. Bourdoux, and S. Pollin, “Phase-noise mitigation at 60 GHz with a novel hybrid MIMO architecture,” in *Proceedings of the 2nd ACM Workshop on Millimeter Wave Networks and Sensing Systems*, ser. mmNets ’18, New York, NY, USA, 2018, p. 39–44.
- [29] A. Papoulis and S. U. Pillai, “Probability, random variables, and stochastic processes,” *McGraw Hill*, 2002.

- [30] M. Slack, "The probability distributions of sinusoidal oscillations combined in random phase," *Journal of the Institution of Electrical Engineers - Part III: Radio and Communication Engineering*, vol. 93, no. 22, pp. 76–86, March 1946.
- [31] W. R. Bennet, "Distribution of the sum of randomly phased components," *Quarterly of Applied Mathematics*, vol. 5, no. 4, p. 385–393, 1948.
- [32] R. H. Clarke, "A Statistical Theory of Mobile-Radio Reception," *Bell System Technical Journal*, vol. 47, no. 6, pp. 957–1000, 8 1968.
- [33] W. Jakes and D. C. Cox, "Microwave mobile communications," *Wiley-IEEE Press*, 1994.
- [34] X. Gao, O. Edfors, F. Tufvesson, and E. G. Larsson, "Massive MIMO in real propagation environments: Do all antennas contribute equally?" *IEEE Transactions on Communications*, vol. 63, no. 11, pp. 3917–3928, Nov 2015.
- [35] J. P. Kermoal, L. Schumacher, K. I. Pedersen, P. E. Mogensen, and F. Frederiksen, "A stochastic MIMO radio channel model with experimental validation," *IEEE Journal on Selected Areas in Communications*, vol. 20, no. 6, pp. 1211–1226, Aug 2002.
- [36] X. Gao, O. Edfors, F. Rusek, and F. Tufvesson, "Massive MIMO performance evaluation based on measured propagation data," *IEEE Transactions on Wireless Communications*, vol. 14, no. 7, pp. 3899–3911, July 2015.
- [37] A. Adhikary, J. Nam, J.-Y. Ahn, and G. Caire, "Joint spatial division and multiplexing—The large-scale array regime," *IEEE Transactions on Information Theory*, vol. 59, no. 10, pp. 6441–6463, 2013.
- [38] J. Salz and J. H. Winters, "Effect of fading correlation on adaptive arrays in digital mobile radio," *IEEE Transactions on Vehicular Technology*, vol. 43, no. 4, pp. 1049–1057, 1994.
- [39] D. S. Shiu, G. J. Foschini, M. J. Gans, and J. M. Kahn, "Fading correlation and its effect on the capacity of multielement antenna systems," *IEEE Transactions on Communications*, vol. 48, no. 3, pp. 502–513, March 2000.
- [40] H. Yin, D. Gesbert, M. Filippou, and Y. Liu, "A coordinated approach to channel estimation in large-scale multiple-antenna systems," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 2, pp. 264–273, February 2013.

-
- [41] A. F. Molisch, "Wireless communications," *John Wiley & Sons*, 2007.
- [42] Z. Jiang, A. F. Molisch, G. Caire, and Z. Niu, "Achievable rates of FDD massive MIMO systems with spatial channel correlation," *IEEE Transactions on Wireless Communications*, vol. 14, no. 5, pp. 2868–2882, May 2015.
- [43] F. Adachi, M. T. Feeney, J. D. Parsons, and A. G. Williamson, "Crosscorrelation between the envelopes of 900 MHz signals received at a mobile radio base station site," *IEE Proc. F - Commun., Radar and Signal Process.*, vol. 133, no. 6, pp. 506–512, 1986.
- [44] P. Zetterberg and B. Ottersten, "The spectrum efficiency of a base station antenna array system for spatially selective transmission," *IEEE Transactions on Vehicular Technology*, vol. 44, no. 3, pp. 651–660, 1995.
- [45] J. Salz and J. H. Winters, "Effect of fading correlation on adaptive arrays in digital mobile radio," *IEEE Transactions on Vehicular Technology*, vol. 43, no. 4, pp. 1049–1057, Nov 1994.
- [46] R. Stridh, "Smart antennas in wireless networks: System issues and performance limits," Ph.D. dissertation, KTH Royal Institute of Technology, 2003.
- [47] R. Kennedy, "Fading dispersive communication channels," *Wiley-Interscience*, 1969.
- [48] R. M. Gray, "Toeplitz and circulant matrices: A review," *Foundations and Trends® in Communications and Information Theory*, vol. 2, no. 3, pp. 155–239, 2006. [Online]. Available: <http://dx.doi.org/10.1561/01000000006>
- [49] 3rd Generation Partnership Project, "*Technical Specification Group Radio Access Network; Spatial channel model for Multiple Input Multiple Output (MIMO) simulations*", Mar. 2017, 3GPP TR 25.996 V14.0.0.
- [50] S. O. Rice, "Mathematical analysis of random noise," *The Bell System Technical Journal*, vol. 23, no. 3, pp. 282–332, July 1944.
- [51] A. Paulraj, R. Roy, and T. Kailath, "Estimation of signal parameters via rotational invariance techniques- ESPRIT," in *Nineteenth Asilomar Conference on Circuits, Systems and Computers*, 1985., Nov 1985, pp. 83–89.
- [52] R. O. Schmidt, "A signal subspace approach to multiple emitter location and spectral estimation," Ph.D. dissertation, 1981.

- [53] S. L. Loyka, "Channel capacity of MIMO architecture using the exponential correlation matrix," *IEEE Communications Letters*, vol. 5, no. 9, pp. 369–371, Sep. 2001.
- [54] A. J. Paulraj and C. B. Papadias, "Space-time processing for wireless communications," *IEEE Signal Processing Magazine*, vol. 14, no. 6, pp. 49–83, Nov 1997.
- [55] M. Matthaiou, P. J. Smith, H. Q. Ngo, and H. Tataria, "Does massive MIMO fail in Ricean channels?" *IEEE Wireless Communications Letters*, vol. 8, no. 1, pp. 61–64, Feb 2019.
- [56] S. M. Kay, "Fundamentals of statistical signal processing: Estimation theory," *Prentice Hall*, 1993.
- [57] G. R. Fowles, *Introduction to modern optics*. Courier Corporation, 1989.
- [58] C. A. Balanis, *Antenna theory: analysis and design*. Wiley-Interscience, 2005.
- [59] H. Asplund, D. Astely, P. von Butovitsch, T. Chapman, M. Frenne, F. Ghasemzadeh, M. Hagström, B. Hogan, G. Jongren, J. Karlsson *et al.*, *Advanced Antenna Systems for 5G Network Deployments: Bridging the Gap Between Theory and Practice*. Academic Press, 2020.
- [60] M. Coldrey, "Modeling and capacity of polarized MIMO channels," in *IEEE Vehicular Technology Conference (VTC Spring)*. IEEE, 2008, pp. 440–444.
- [61] P.-S. Kildal, *Foundations of antenna engineering: a unified approach for line-of-sight and multipath*. Artech House, 2015.
- [62] H. Asplund, J.-E. Berg, F. Harrysson, J. Medbo, and M. Riback, "Propagation characteristics of polarized radio waves in cellular communications," in *2007 IEEE 66th Vehicular Technology Conference*. IEEE, 2007, pp. 839–843.
- [63] W. L. Stutzman, *Polarization in electromagnetic systems*. Artech house, 2018.
- [64] R. Bhagavatula, C. Oestges, and R. W. Heath, "A new double-directional channel model including antenna patterns, array orientation, and depolarization," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 5, pp. 2219–2231, 2010.

-
- [65] V. Degli-Esposti, V.-M. Kolmonen, E. M. Vitucci, and P. Vainikainen, "Analysis and modeling on co-and cross-polarized urban radio propagation for dual-polarized MIMO wireless systems," *IEEE transactions on antennas and propagation*, vol. 59, no. 11, pp. 4247–4256, 2011.
- [66] C. Oestges, B. Clerckx, M. Guillaud, and M. Debbah, "Dual-polarized wireless communications: From propagation models to system performance evaluation," *IEEE Trans. Wireless Commun.*, vol. 7, no. 10, pp. 4019–4031, 2008.
- [67] I. Union, "IMT traffic estimates for the years 2020 to 2030," *Report ITU*, vol. 2370, 2015.
- [68] S. Buzzi, I. Chih-Lin, T. E. Klein, H. V. Poor, C. Yang, and A. Zappone, "A survey of energy-efficient techniques for 5g networks and challenges ahead," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 4, pp. 697–709, 2016.
- [69] C. Liaskos, S. Nie, A. Tsioliaridou, A. Pitsillides, S. Ioannidis, and I. Akyildiz, "A new wireless communication paradigm through software-controlled metasurfaces," *IEEE Communications Magazine*, vol. 56, no. 9, pp. 162–169, 2018.
- [70] E. Björnson, L. Sanguinetti, H. Wymeersch, J. Hoydis, and T. L. Marzetta, "Massive mimo is a reality—what is next?: Five promising research directions for antenna arrays," *Digital Signal Processing*, vol. 94, pp. 3–20, 2019.
- [71] E. Björnson, Ö. Özdogan, and E. G. Larsson, "Reconfigurable intelligent surfaces: Three myths and two critical questions," *IEEE Communications Magazine*, vol. 58, no. 12, pp. 90–96, 2020.
- [72] V. S. Asadchy, M. Albooyeh, S. N. Tsvetkova, A. Díaz-Rubio, Y. Ra'di, and S. Tretyakov, "Perfect control of reflection and refraction using spatially dispersive metasurfaces," *Physical Review B*, vol. 94, no. 7, p. 075142, 2016.
- [73] N. M. Estakhri and A. Alu, "Wave-front transformation with gradient metasurfaces," *Physical Review X*, vol. 6, no. 4, p. 041008, 2016.
- [74] X. Wan, M. Q. Qi, T. Y. Chen, and T. J. Cui, "Field-programmable beam reconfiguring based on digitally-controlled coding metasurface," *Scientific reports*, vol. 6, no. 1, pp. 1–8, 2016.
- [75] H. Yang, X. Cao, F. Yang, J. Gao, S. Xu, M. Li, X. Chen, Y. Zhao, Y. Zheng, and S. Li, "A programmable metasurface with dynamic polarization, scattering and focusing control," *Scientific reports*, vol. 6, no. 1, pp. 1–11, 2016.

- [76] S. V. Hum and J. Perruisseau-Carrier, “Reconfigurable reflectarrays and array lenses for dynamic antenna beam control: A review,” *IEEE Transactions on Antennas and Propagation*, vol. 62, no. 1, pp. 183–198, 2013.
- [77] B. Zheng and R. Zhang, “Intelligent reflecting surface-enhanced ofdm: Channel estimation and reflection optimization,” *IEEE Wireless Communications Letters*, vol. 9, no. 4, pp. 518–522, 2019.
- [78] E. Björnson, “Optimizing a binary intelligent reflecting surface for ofdm communications under mutual coupling,” *arXiv preprint arXiv:2106.04280*, 2021.
- [79] Q. Wu, S. Zhang, B. Zheng, C. You, and R. Zhang, “Intelligent reflecting surface aided wireless communications: A tutorial,” *IEEE Transactions on Communications*, 2021.
- [80] E. Björnson, O. Özdogan, and E. G. Larsson, “Intelligent reflecting surface vs. decode-and-forward: How large surfaces are needed to beat relaying?” *IEEE Wireless Communications Letters*, pp. 1–1, 2019.
- [81] Y. Liu, X. Liu, X. Mu, T. Hou, J. Xu, M. Di Renzo, and N. Al-Dhahir, “Reconfigurable intelligent surfaces: Principles and opportunities,” *IEEE Communications Surveys & Tutorials*, 2021.
- [82] S. Zhang and R. Zhang, “Capacity characterization for intelligent reflecting surface aided mimo communication,” *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 8, pp. 1823–1838, 2020.
- [83] H. Wymeersch, J. He, B. Denis, A. Clemente, and M. Juntti, “Radio localization and mapping with reconfigurable intelligent surfaces: Challenges, opportunities, and research directions,” *IEEE Vehicular Technology Magazine*, vol. 15, no. 4, pp. 52–61, 2020.
- [84] A. Bourdoux, A. N. Barreto, B. van Liempd, C. de Lima, D. Dardari, D. Belot, E.-S. Lohan, G. Seco-Granados, H. Srieddeen, H. Wymeersch *et al.*, “6g white paper on localization and sensing,” *arXiv preprint arXiv:2006.01779*, 2020.
- [85] X. Ma, Z. Chen, W. Chen, Z. Li, Y. Chi, C. Han, and S. Li, “Joint channel estimation and data rate maximization for intelligent reflecting surface assisted terahertz mimo communication systems,” *IEEE Access*, vol. 8, pp. 99 565–99 581, 2020.

- [86] C. Chaccour, M. N. Soorki, W. Saad, M. Bennis, and P. Popovski, "Risk-based optimization of virtual reality over terahertz reconfigurable intelligent surfaces," in *ICC 2020-2020 IEEE International Conference on Communications (ICC)*. IEEE, 2020, pp. 1–6.
- [87] Y. Tang, G. Ma, H. Xie, J. Xu, and X. Han, "Joint transmit and reflective beamforming design for irs-assisted multiuser miso swipt systems," in *ICC 2020-2020 IEEE International Conference on Communications (ICC)*. IEEE, 2020, pp. 1–6.
- [88] C. Pan, H. Ren, K. Wang, M. El Kashlan, A. Nallanathan, J. Wang, and L. Hanzo, "Intelligent reflecting surface aided mimo broadcasting for simultaneous wireless information and power transfer," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 8, pp. 1719–1734, 2020.
- [89] X. Yu, D. Xu, Y. Sun, D. W. K. Ng, and R. Schober, "Robust and secure wireless communications via intelligent reflecting surfaces," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 11, pp. 2637–2652, 2020.
- [90] X. Guan, Q. Wu, and R. Zhang, "Intelligent reflecting surface assisted secrecy communication: Is artificial noise helpful or not?" *IEEE Wireless Communications Letters*, vol. 9, no. 6, pp. 778–782, 2020.
- [91] T. Bai, C. Pan, Y. Deng, M. El Kashlan, A. Nallanathan, and L. Hanzo, "Latency minimization for intelligent reflecting surface aided mobile edge computing," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 11, pp. 2666–2682, 2020.
- [92] S. Hua, Y. Zhou, K. Yang, Y. Shi, and K. Wang, "Reconfigurable intelligent surface for green edge inference," *IEEE Transactions on Green Communications and Networking*, vol. 5, no. 2, pp. 964–979, 2021.
- [93] S. Li, B. Duo, X. Yuan, Y.-C. Liang, and M. Di Renzo, "Reconfigurable intelligent surface assisted uav communication: Joint trajectory design and passive beamforming," *IEEE Wireless Communications Letters*, vol. 9, no. 5, pp. 716–720, 2020.
- [94] D. Ma, M. Ding, and M. Hassan, "Enhancing cellular communications for uavs via intelligent reflective surface," in *2020 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2020, pp. 1–6.
- [95] "Empowering vertical industries through 5G networks current status and future trends," *5G PPP Technology Board and 5G IA Verticals Task Force*, 2020.

- [96] T. O'shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Transactions on Cognitive Communications and Networking*, vol. 3, no. 4, pp. 563–575, 2017.
- [97] E. Bjornson and P. Giselsson, "Two applications of deep learning in the physical layer of communication systems [lecture notes]," *IEEE Signal Processing Magazine*, vol. 37, no. 5, pp. 134–140, 2020.
- [98] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural networks*, vol. 2, no. 5, pp. 359–366, 1989.
- [99] A. Zappone, M. Di Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, ai-based, or both?" *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7331–7376, 2019.
- [100] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning*. MIT press, 2016.
- [101] H. Huang, S. Guo, G. Gui, Z. Yang, J. Zhang, H. Sari, and F. Adachi, "Deep learning for physical-layer 5g wireless techniques: Opportunities, challenges and solutions," *IEEE Wireless Communications*, vol. 27, no. 1, pp. 214–222, 2019.
- [102] D. Neumann, T. Wiese, and W. Utschick, "Learning the MMSE channel estimator," *IEEE Trans. Signal Process.*, vol. 66, no. 11, pp. 2905–2917, 2018.
- [103] F. D. Calabrese, L. Wang, E. Ghadimi, G. Peters, L. Hanzo, and P. Soldati, "Learning radio resource management in rans: Framework, opportunities, and challenges," *IEEE Communications Magazine*, vol. 56, no. 9, pp. 138–145, 2018.
- [104] R. Li, Z. Zhao, X. Zhou, G. Ding, Y. Chen, Z. Wang, and H. Zhang, "Intelligent 5g: When cellular networks meet artificial intelligence," *IEEE Wireless communications*, vol. 24, no. 5, pp. 175–183, 2017.
- [105] A. M. Elbir and K. V. Mishra, "A survey of deep learning architectures for intelligent reflecting surfaces," *arXiv preprint arXiv:2009.02540*, 2020.

Included Papers

Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

<https://doi.org/10.3384/9789179291655>

Other Recently Published Theses From
The Division of Communication Systems
Department of Electrical Engineering (ISY)
Linköping University, Sweden

Amin Ghazanfari, *Multi-Cell Massive MIMO: Power Control and Channel Estimation*, Linköping Studies in Science and Technology. Dissertations, No. 2142, 2021

Ziya Gülgün, *Physical Layer Security Issues in Massive MIMO and GNSS*, Linköping Studies in Science and Technology. Licentiate Thesis, No. 1899, 2021

Özgecan Özdoğan, *Analysis of Cellular and Cell-Free Massive MIMO with Rician Fading*, Linköping Studies in Science and Technology. Licentiate Thesis, No. 1870, 2020

Ema Becirovic, *On Massive MIMO for Massive Machine-Type Communications*, Linköping Studies in Science and Technology. Licentiate Thesis, No. 1868, 2020.

Daniel Verenzuela, *Exploring Alternative Massive MIMO Designs: Superimposed Pilots and Mixed-ADCs*, Linköping Studies in Science and Technology. Dissertations, No. 2041, 2020.

Trịnh Văn Chiển, *Spatial Resource Allocation in Massive MIMO Communication: From Cellular to Cell-Free*, Linköping Studies in Science and Technology. Dissertations, No. 2036, 2020.

Amin Ghazanfari, *Power Control for Multi-Cell Massive MIMO*, Linköping Studies in Science and Technology. Licentiate Thesis, No. 1852, 2019.

Giovanni Interdonato, *Signal Processing Aspects of Cell-Free Massive MIMO*, Linköping Studies in Science and Technology. Licentiate Thesis, No. 1817, 2018.

Marcus Karlsson, *Blind Massive MIMO Base Stations: Downlink Transmission and Jamming*, Linköping Studies in Science and Technology. Dissertations, No. 1950, 2018.

Victor Hei Cheng, *Optimizing Massive MIMO: Precoder Design and Power Allocation*, Linköping Studies in Science and Technology. Dissertations, No. 1929, 2018.

Christopher Mollén, *High-End Performance with Low-End Hardware: Analysis of Massive MIMO Base Station Transceivers*, Linköping Studies in Science and Technology. Dissertations, No. 1896, 2017.

FACULTY OF SCIENCE AND ENGINEERING

Linköping Studies in Science and Technology, Dissertation No. 2199, 2022

Division of Communication Systems, Department of Electrical Engineering

Linköping University
SE-581 83 Linköping, Sweden

www.liu.se