

**ARRAY PROCESSING AND OPTIMIZATION TECHNIQUES OF
BEAMFORMING AND RESOURCE ALLOCATION FOR ENHANCED
SPECTRAL EFFICIENCY IN 5G AND BEYOND SYSTEMS**

A DISSERTATION SUBMITTED TO
THE GRADUATE SCHOOL OF
ENGINEERING AND NATURAL SCIENCES
OF ISTANBUL MEDIPOL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN
ELECTRICAL, ELECTRONICS ENGINEERING AND CYBER SYSTEMS

By

Nann Win Moe Thet

June, 2021

ARRAY PROCESSING AND OPTIMIZATION TECHNIQUES OF BEAMFORMING
AND RESOURCE ALLOCATION FOR ENHANCED SPECTRAL EFFICIENCY IN
5G AND BEYOND SYSTEMS

By Nann Win Moe Thet

21 June 2021

We certify that we have read this dissertation and that in our opinion it is fully adequate,
in scope and in quality, as a dissertation for the degree of Doctor of Philosophy.

Assoc. Prof. Dr. Mehmet Kemal Özdemir (Advisor)

Assoc. Prof. Dr. Ali Emre Pusane

Assoc. Prof. Dr. Ertuğrul Başar

Prof. Dr. Hakan Tozan

Assist. Prof. Dr. Tuncer Baykaş

Approved by the Graduate School of Engineering and Natural Sciences:

Assoc. Prof. Dr. Yasemin Yüksel Durmaz

Director of the Graduate School of Engineering and Natural Sciences



I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Signature :

Name, Surname: NANN WIN MOE THET

ACKNOWLEDGEMENT

First and foremost, I would like to express my most valuable appreciation to my Master's and Ph.D. advisor Assoc. Prof. Dr. Mehmet Kemal Özdemir for his great support and contribution. Without his patience and sacrificing hours for me, this thesis will never be written. His wide knowledge, plentiful experience, continuous guidance, and encouragement motivated me to commit myself to research and also pursue an academic career in my future endeavors.

I would like to extend my sincere thanks to the committee members of my Ph.D. thesis: Assist. Prof. Dr. Tuncer Baykaş, Prof. Dr. Hakan Tozan, Assoc. Prof. Dr. Ertuğrul Başar, and Assoc. Prof. Dr. Ali Pusane for their constructive comments and valuable suggestions on my research works and thesis.

I wish to thank the Graduate School Director Assoc. Prof. Dr. Yasemin Yüksel Durmaz and the staffs of the secretary office at Engineering and Natural Sciences Department for technical support throughout my stay in Medipol University. I am also grateful to my fellow lab colleagues and friends in Medipol University. I have learned a lot from each of them throughout the years, and I really appreciate their companions, help, and ideas. Their kind support and friendship have made my study and life in Turkey a wonderful time.

I would also like to acknowledge that this thesis work is supported in part by the Scientific and Technological Research Council of Turkey (TUBITAK) under Grant No. 215E316 and fellowship under TUBITAK-BİDEB 2215: Graduate Scholarship Programme for International Students. Without these financial supports, I would not be able to complete my Ph.D. study.

Finally, I would like to express my gratitude to my parents and younger siblings for their tremendous support and encouragement throughout my studies. Special thanks to my sister who has help me make my daily life easier in Turkey.

Nann Win Moe Thet
June, 2021

CONTENTS

	<u>Page</u>
ACKNOWLEDGEMENT	iv
CONTENTS	v
LIST OF FIGURES.....	viii
LIST OF TABLES	x
LIST OF SYMBOLS	xi
ABBREVIATIONS	xii
ÖZET	xvi
ABSTRACT	xix
1. INTRODUCTION	1
1.1. Background	1
1.2. Motivation And Thesis Contributions	3
1.2.1. Reduced-rank joint estimation of DoA with mutual coupling	4
1.2.2. Impact of mutual coupling on power-domain non-orthogonal multiple access (NOMA)	5
1.2.3. Performance analysis of user scheduling in massive MIMO with fast moving users	6
1.2.4. Low-complexity deep learning-based beamforming in MISO systems	7
1.2.5. Joint overlap ratios and power allocation with user fairness in partial non-orthogonal multiple access (PNOMA)	8
1.2.6. Partial-beam non-orthogonal multiple access (PB-NOMA) with fuzzy clustering.....	9
1.2.7. Outage probability analysis of reconfigurable intelligent surface-enabled coordinated multi-points NOMA networks.....	9
2. THEORETICAL PART	11
2.1. Direction-of-Arrival (DoA) Estimation.....	11
2.1.1. Conventional beamformer	12
2.1.2. Adaptive beamformer	13
2.1.3. Subspace-based techniques	14
2.2. Mutual Coupling.....	14
2.2.1. Mutual coupling matrix (MCM) based on array configuration	15
2.3. Array steering vector	17
2.4. Channel model	19
2.5. Effective steering vector and transmit beam power with MC	19
2.6. Beamforming	20
2.6.1. Analog beamforming.....	20
2.6.2. Digital beamforming	22
2.6.3. Hybrid beamforming.....	23
2.7. Multi-user system.....	25
2.7.1. Signal model.....	25
2.7.2. Two-stage precoder	26
2.7.3. User grouping and scheduling	27
2.8. Non-Orthogonal Multiple Access.....	29
2.8.1. Downlink NOMA transmission	30
2.8.2. Uplink NOMA transmission.....	31

2.9.	Partial Non-Orthogonal Multiple Access (P-NOMA)	32
2.10.	Related Works	34
2.10.1.	Direction-of-arrival estimation and mutual coupling	34
2.10.2.	Massive MIMO and beamforming	36
2.10.3.	Non-orthogonal multiple access (NOMA) with emerging technologies	38
3.	EXPERIMENTAL PART	41
3.1.	Reduced-Rank Joint Estimation of DoA with Mutual Coupling	41
3.1.1.	The proposed algorithm	42
3.1.2.	Simulation setup	46
3.2.	Impact Of Mutual Coupling On Power-Domain Non-Orthogonal Multiple Access (NOMA)	47
3.2.1.	Achievable sum-rate in the presence of MC	47
3.2.2.	Mutual coupling compensation	50
3.2.3.	Simulation setup	51
3.3.	Performance Analysis of User Scheduling in Massive MIMO with Fast Moving Users	52
3.3.1.	Channel model with doppler effect	53
3.3.2.	Simulation setup	53
3.4.	Low-Complexity Deep Learning-Based Beamforming in MISO Systems	54
3.4.1.	System model	55
3.4.2.	Problem formulation	56
3.4.3.	Proposed deep learning-based beamforming model	56
3.4.4.	Simulation setup	58
3.5.	Joint Overlap Ratios and Power Allocation with User Fairness in Partial Non-Orthogonal Multiple Access (P-NOMA)	60
3.5.1.	Joint allocation of overlap ratios and power coefficient	60
3.5.2.	Simulation setup	61
3.6.	Partial-Beam Non-Orthogonal Multiple Access (PB-NOMA) with Fuzzy Clustering	62
3.6.1.	Proposed partial-beam NOMA system	63
3.6.2.	Sum-rate comparison between P-NOMA and PB-NOMA	66
3.6.3.	User clustering and pairing	67
3.6.4.	Simulation setup	69
3.7.	Outage Probability Analysis of Reconfigurable Intelligent Surface-Enabled Coordinated Multi-points NOMA Networks	70
3.7.1.	System model	71
3.7.2.	Signal model	72
3.7.3.	Channel statistics	73
3.7.4.	Outage probability (OP) analysis	75
3.7.5.	Simulation setup	76
4.	RESULTS AND DISCUSSION	77
4.1.	Reduced-Rank Joint Estimation of DoA with Mutual Coupling	77
4.2.	Impact of Mutual Coupling on Power-Domain Non-Orthogonal Multiple Access (NOMA)	81
4.2.1.	Antenna array beam pattern in the presence of MC	82
4.2.2.	Uplink NOMA with ULA	84
4.2.3.	Downlink NOMA	84

4.3.	Performance Analysis of User Scheduling in Massive MIMO with Fast Moving Users	91
4.4.	Low-Complexity Deep Learning-Based Beamforming in MISO Systems .	93
4.5.	Joint Overlap Ratios and Power Allocation with User Fairness in Partial Non-Orthogonal Multiple Access (P-NOMA)	96
4.6.	Partial-Beam Non-Orthogonal Multiple Access (PB-NOMA) with Fuzzy Clustering	98
4.7.	Outage Probability Analysis of Reconfigurable Intelligent Surface-Enabled Coordinated Multi-points NOMA Networks	101
5.	CONCLUSION AND FUTURE WORK.....	103
5.1.	Conclusions	103
5.2.	Future Works.....	106
5.2.1.	Extensions of the current works	106
5.2.2.	Future directions	107
	BIBLIOGRAPHY.....	110
	APPENDIX A.....	125
	CURRICULUM VITAE.....	129

LIST OF FIGURES

Figure 2.1:	A uniform linear arrays system model.	11
Figure 2.2:	Uniform circular array geometry: a) 3-Dimensional (3-D) view, b) Top view in XY-plane.	18
Figure 2.3:	Uniform circular array geometry with staggered Uniform Circular Array (UCA) at $z = \lambda/4$: a) 3-D view, b) Top view in XY-plane.	18
Figure 2.4:	Beamforming structures for spatial multiplexing: a) analog beamforming, b) digital beamforming, c) hybrid beamforming.	21
Figure 2.5:	DL Multiple-User (MU) massive Multiple-Input Multiple-Output (MIMO) system with precoding matrix $\mathbf{F}$	25
Figure 2.6:	MISO-NOMA system model, where Base Station (BS) serves K Non-Orthogonal Multiple Access (NOMA)-User Terminalss (UTs). ...	30
Figure 2.7:	P-NOMA system model. B_n is fully occupied by near UT when $\beta = 0$, and B_f is fully utilized by far UT when $\alpha = 0$	33
Figure 3.1:	Summary of the proposed algorithm.	46
Figure 3.2:	Single-User (SU)-Multiple-Input Single-Output (MISO) system with hybrid beamforming.	55
Figure 3.3:	Data preparation: $h_{e_k}^{c_1}$ and $h_{e_k}^{c_2}$ are the first and second components of the k^{th} formatted input, h_{e_k} , for all k	57
Figure 3.4:	The proposed Beamforming Neural Network (BFNN) architecture.	58
Figure 3.5:	Partial-beam NOMA system model with overlapped clusters, where near UTs in group 1 and group 2 partially belong to each other's group.	63
Figure 3.6:	RIS-enabled CoMP-NOMA system model.	71
Figure 4.1:	Comparison of spatial power spectra at Signal-to-Noise Ratio (SNR)= 20 dB.	77
Figure 4.2:	The RMSEs of Direction-of-Arrival (DoA) versus SNR at snapshot number= 20.	78
Figure 4.3:	Probability of success versus SNR at snapshot number= 20.	79
Figure 4.4:	Average CPU time versus antenna array size, N_t at SNR=20 dB and $K=20$	81
Figure 4.5:	Normalized YZ-plane pattern with nearest UT-based beamformer, employing Uniform Linear Array (ULA) with $N_t = 16$ and $d = 0.5\lambda$, MOM/EM simulation.	82
Figure 4.6:	Normalized XY-plane pattern with nearest UT-based beamformer, employing: a) UCA with $N_t = 8$ and $r = 0.25\lambda$, b) staggered 3-D UCA in XY-plane, where the outer circle has $N_1 = 4$ with $r_1 = 0.5\lambda$, and the inner circle has $N_2 = 3$ with $r_2 = 0.4\lambda$ at $z = \lambda/4$, generated by MOM/EM simulation.	83
Figure 4.7:	Received power for first and second UTs at the BS with the transmit power $p_k = 6.05$ dBm using a) Electromotive Force (EMF)/MATLAB simulation, b) MOM/EM simulation.	84
Figure 4.8:	Total achievable sum-rate of Uplink (UL) NOMA using ULA with $N_t = 16$ and $d = 0.5\lambda$	85
Figure 4.9:	Channel gain resulting from nearest UT-based beamforming in ULA with $N_t = 16$, $d = 0.5\lambda$ and $\theta = [68^\circ, 60^\circ]$	86
Figure 4.10:	Total achievable sum-rate of Downlink (DL) NOMA using ULA with $N_t = 16$ and $d = 0.5\lambda$	86

Figure 4.11: a) Normalized beam pattern, b) channel gain, c) total achievable sum-rate of DL NOMA with nearest UT-based analog beamformer $\mathbf{v} = \mathbf{a}(\phi_1)$ using UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [68^\circ, 60^\circ, 50^\circ, 80^\circ]$.	87
Figure 4.12: Channel gain resulting from near UT-based beamforming in UCA with $N_t = 8$, $d = 0.25\lambda$ and $\phi = [113^\circ, 100^\circ, 90^\circ, 84^\circ]$, generated by a) EMF/MATLAB simulation, b) Method-of-Moments (MOM)/EMF simulation.	88
Figure 4.13: Total achievable sum-rate of DL NOMA using UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [113^\circ, 100^\circ, 90^\circ, 84^\circ]$ for the patterns generated by MOM and EMF methods.	89
Figure 4.14: a) Normalized beam pattern, b) channel gain at all directions, c) total achievable sum-rate of DL NOMA with using combined near UT-based analog beamforming weights in 3-D UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [68^\circ, 60^\circ, 50^\circ, 80^\circ]$.	90
Figure 4.15: Sum-rate comparison of scheduling versus K at SNR = 15 dB and $T_{frame} = 6$ ms.	91
Figure 4.16: Sum-rate comparison of scheduling versus SNR at $K = 100$ and $T_{frame} = 6$ ms.	92
Figure 4.17: Sum-rate comparison of scheduling versus T_{frame} at SNR = 15 dB with $K = 100$.	93
Figure 4.18: Spectral efficiency comparisons of conventional beamforming approaches and BFNNs with different data representations at PNR = 0 dB.	95
Figure 4.19: Spectral efficiency comparisons of conventional beamforming approaches and BFNNs for different L_{est} at PNR = 20 dB.	96
Figure 4.20: Contour graphs of a) Total sum rate, b) User fairness, c) Power allocation coefficient, with respect to Overlap Ratios (ORs) under $F_t = 0.7$, $d_r = 1 : 2$, $SNR_k = 10$ dB, using exhaustive search.	97
Figure 4.21: Comparison of a) Total sum rate, b) Jain's user fairness, based on distance ratio.	98
Figure 4.22: Contour graphs of total sum-rate for the Partial-Beam NOMA (PB-NOMA) signal model with $\alpha_g = \beta_g = 0.7$ in a) group $g = 1$, and b) group $g = 2$, with respect to Overlapping Beam Ratio (OBR)s at $P_m = 10$ dB and $\sigma_m^2 = -2$ dB.	99
Figure 4.23: The effect of $(\alpha_g, \epsilon_{g'})$ on the sum-rates of the UTs in each group with $\beta_1 = \beta_2 = 0.7$ a) At $\alpha_2 = 0.7$ and $\epsilon_1 = 0$, b) At $\alpha_1 = 0.7$ and $\epsilon_2 = 0$.	100
Figure 4.24: Sum-rate comparison between PB-NOMA and Partial NOMA (P-NOMA) at $\beta_1 = \beta_2 = 0.7$ for a) Group 1 with $\epsilon_1 = 0$, b) Group 2 with $\epsilon_2 = 0$.	101
Figure 4.25: Outage probability of all UTs in traditional Joint Transmission Coordinated Multi-points (JT-CoMP)-NOMA system without Reconfigurable Intelligent Surface (RIS); <i>Direct</i> case vs SNR.	102
Figure 4.26: Outage probability of U_2 in different cases vs SNR.	102

LIST OF TABLES

Table 3.1: Simulation parameters in NOMA system with MC.....	52
Table 3.2: Simulation parameters in multi-user system with fast moving users.	54
Table 3.3: Hyper-parameters for CNN-BFNN model.	59
Table 3.4: Simulation parameters of the dataset.	59
Table 3.5: Simulation parameters in P-NOMA system.....	63
Table 3.6: Simulation parameters in PB-NOMA system.....	70
Table 3.7: Simulation parameters in CoMP-NOMA with RIS.....	76
Table 4.1: Complexity comparison.	94



LIST OF SYMBOLS

η	:Path-loss exponent
$\mathcal{CN}(a, b)$	:Circularly symmetric complex Gaussian distribution with mean a and variance b
$(\cdot)^H$	:Hermitian (conjugate transpose)
$(\cdot)^T$	:Transpose
$\mathcal{U}(c, d)$	:Uniform distribution between c and d bounds
$\text{tr}(\mathbf{A})$	:Trace of matrix $\mathbf{A}$
$\text{Toeplitz}(\mathbf{A}, \mathbf{A})$	:Symmetric Toeplitz matrix $\mathbf{A}$
$\text{blkdiag}(\mathbf{A}, \mathbf{A})$	:Block diagonal matrix of matrix $\mathbf{A}$
$\ \cdot\ _F$	:Frobenius norm
$ \cdot $	:Absolute value
$\mathbf{I}_N$	: $N \times N$ identity matrix
σ	:Noise standard deviation
$\mathbf{n}$	:AWGN
N_0	:Noise power density
$\mathbf{B}$	:Bandwidth
$\mathbf{C}$	:Mutual coupling matrix
$\mathbf{c}$	:Mutual coupling vector
$\mathbf{Z}$	:Mutual coupling impedance matrix
$\mathbf{A}$	:Array manifold matrix
$\mathbf{a}(\theta)$	:Steering vector at angle θ
$\mathbf{R}$	:Covariance matrix
$\mathbf{h}$	:Channel coefficient vector
h	:SISO channel coefficient
λ	:Wavelength
$\Upsilon[\cdot]$	:Unitary matrix of eigen decomposition
Δ_{sub}	:Frequency subcarrier spacing
γ	:Power allocation coefficient
ϕ	:Azimuth and elevation angles of DoA/DoD
θ	:Elevation angles of DoA/DoD
N_t	:Number of antenna elements
K	:Number of user terminals (UTs)

ABBREVIATIONS

1-D	:1-Dimension
2-D	:2-Dimensional
3-D	:3-Dimensional
4G	:Fourth-Generation
5G	:Fifth-Generation
A/Φ	:Amplitude and Phase
AB	:Analog Beamforming
AC	:Activation
Adam	:Adaptive Moment
ADC	:Analog-to-Digital-Converter
AI	:Artificial Intelligent
AN	:Artificial Noise
AWGN	:Additive White Gaussian Noise
BFNN	:Beamforming Neural Network
BN	:Batch Normalization
BPCU	:Bits Per Channel Use
BS	:Base Station
CDF	:Cumulative Distribution Function
CL	:Convolutional Layer
CLT	:Central Limit Theorem
CNN	:Convolutional Neural Network
CoMP	:Coordinated Multi-Points
CSI	:Channel State Information
DAC	:Digital-to-Analog-Converter
DB	:Digital Beamforming
DL	:Downlink
DNN	:Deep Neural Networks
DoA	:Direction-of-Arrival
DoD	:Direction-of-Departure
DoF	:Degrees of Freedom
EE	:Energy Efficiency
EM	:Electromagnetic
EMF	:Electromotive Force
ESOM	:Element-wise Successive Order Merging
ESPRIT	:Estimation of Signal Parameters via Rotational Invariance Techniques
EVD	:Eigen Value Decomposition

FBSS	:Forward Backward Spatial Smoothing
FC	:Fully-Connected
FCM	:Fuzzy C-means
FCNN	:Fully-Connected Neural Network
FD	:Fully-Digital
FDD	:Frequency Division Duplex
FFT	:Fast Fourier Transform
FLOPs	:Floating-Point Operations
FOR	:Far UT's Overlap Ratio
HB	:Hybrid Beamforming
i.i.d	:Independent and Identically Distributed
ICI	:Inter-Cell Interference
IQ	:In-phase and Quadrature
JIO	:Joint Iterative Optimization
JT-CoMP	:Joint Transmission Coordinated Multi-points
LOS	:Line-of-Sight
LTE	:Long-Term Evolution
MA	:Multiple Access
MC	:Mutual Coupling
MCM	:Mutual Coupling Matrix
MF	:Matched Filter
MIMO	:Multiple-Input Multiple-Output
MISO	:Multiple-Input Single-Output
MMSE	:Minimum-Mean-Square-Error
mmWave	:Millimeter Wave
MO	:Manifold Optimization
MOM	:Method-of-Moments
MRT	:Maximum Ratio Transmission
MSE	:Mean-Square-Error
MU	:Multiple-User
MUSIC	:Multiple Signal Classification
MV	:Minimum Variance
NOMA	:Non-Orthogonal Multiple Access
Non-LOS	:Non-Line-of-Sight
NOR	:Near UT's Overlap Ratio
OBR	:Overlapping Beam Ratio
OFDMA	:Orthogonal Frequency-Division Multiple Access

OMA	:Orthogonal Multiple Access
OMP	:Orthogonal Matching Pursuit
OP	:Outage Probability
OR	:Overlap Ratio
P-NOMA	:Partial NOMA
PA	:Power Allocation
PB-NOMA	:Partial-Beam NOMA
PCP	:Poisson cluster process
PE-Alt	:Alternating Minimization Algorithm using Phase Extraction
PL	:Path-Loss
PLS	:Physical Layer Security
PNR	:Pilot-to-Noise Power Ratio
PSs	:Phase Shifters
QoS	:Quality of Service
RF	:Radio-Frequency
RIS	:Reconfigurable Intelligent Surface
RMSE	:Root-Mean-Square-Error
RV	:Random Variable
Rx	:Receiver
SE	:Spectral Efficiency
SGD	:Stochastic Gradient Descent
SIC	:Successive Interference Cancellation
SINR	:Signal-to-Interference-plus-Noise Ratio
SNOI	:Signal-Not-of-Interest
SNR	:Signal-to-Noise Ratio
SOI	:Signal-Of-Interest
SU	:Single-User
SUS	:Semi-orthogonal User Selection
SVD	:Singular Value Decomposition
Tanh	:Hyperbolic Tangent
Tx	:Transmitter
UAV	:Unmanned Aerial Vehicle
UCA	:Uniform Circular Array
UL	:Uplink
ULA	:Uniform Linear Array
ULA	:Uniform Linear Array
URA	:Uniform Rectangular Array

UT	:User Terminals
VGA	:Variable Gain Amplifier
WLD	:Weighted Likelihood
ZF	:Zero-Forcing
ZFB	:Zero-Forcing Beamforming



5G VE ÖTESİ SİSTEMLERİNİN HÜZMELEME VE SPEKTRAL VERİMLİLİĞİNİN VEKTÖR İŞLEME VE OPTİMİZASYON İLE GERÇEKLEŞTİRİLMESİ

ÖZET

Nann Win Moe Thet

Elektrik-Elektronik Mühendisliği ve Siber Sistemler, Doktora

Tez Danışmanı: Assoc. Prof. Dr. Mehmet Kemal Özdemir

21 Haziran 2021

Beşinci Nesil (5G) ve ötesi iletişim sistemleri, kablosuz veri trafiği talebinin hızla artması, daha hızlı veri iletimi ve devasa cihaz bağlantılarının bulunduğu durumlar için kullanılması muhtemel teknolojiler arasında yer almaktadır. Dizisel sinyal işleme, büyük ölçekli anten sistemlerinin 5G ve ötesinde kablosuz ağlarda kullanımı durumlarında, hüzme oluşturma ve sinyal Varış Yönünün (DoA) kestiriminde önemli bir rol oynar. Anten sayısındaki artış, yüksek veri hızı potansiyeline sahip olsa da, en nihayetinde yüksek sayıdaki anten kullanımı, maliyet ve hesaplama karmaşıklığını artırır. Bu nedenle bu tez, hesaplama karmaşıklık sorununu ve 5G ve ötesi sistemler için belirli bir bant genişliğinde yüksek bir veri hızı elde etmenin zorluklarını ele almaktadır. Esasen, bu tez 5G sistemlerinin üç ana yönüne odaklanmaktadır: DoA tahmini, hüzme oluşturma ve Ortogonal Olmayan Çoklu Erişim (NOMA), ilgili karmaşıklık ve spektral verimlilik (SE) sorunları.

Bu tez ilk olarak, faz-uyumlu sinyaller için Düzgün Doğrusal Dizi (ULA) şeklindeki anten yapısının bilinmeyen karşılıklı bağlaşımlar (MC) durumu için, DoA kestirimini bir düşük rank yöntemi ile sunar. Önerilen yöntem, Ortak Yinelemeli Alt Uzay Optimizasyonu (JIO) ve Minimum Varyans (MV) tabanlı MC otomatik kalibrasyonunu temel alır ve tutarlı sinyaller, İleri Geriye Uzamsal Düzeltme (FBSS) JIO işlemi ile entegre edilerek ilişkilendirilir. Önerilen yöntemin performansı, kök ortalama kare hatası, ve başarı olasılığı açısından analiz edildi ve ayrıca karmaşıklık karşılaştırması Merkezi İşlem Birimi (CPU) çalışma süresine göre değerlendirildi.

İkincil olarak, bu tezde NOMA sisteminin ulaşılabilir toplam veri oranı üzerindeki karşılıklı bağlaşımlar etkisi incelenmiştir. Baz istasyonunda (BS) ULA, 2 Boyutlu (2D) Doğrusal Dairesel Dizi (UCA) ve kademeli 3 Boyutlu (3D) UCA gibi farklı anten konfigürasyonları ayrı ayrı kullanılarak ışın desenleri ve sistem toplam veri hızı analiz gerçekleştirilmiştir. Farklı anten yapıları için Elektromotor Kuvvete (EMF) dayalı karşılıklı eşleşme ifadeleri de elde edilmiştir. Hem uplink (UL) hem de downlink (DL) iletimleri gerçekleştirilerek, MC kompanzasyonu olan ve olmayan ilgili toplam veri oran performansları incelenmiştir.

Üçüncül olarak, hızlı sönmeme kanalına sahip Frekans Bölmeli Çift Yönlü (FDD) masif MIMO sistemlerinde kullanıcı gruplamasının ve çizelgelemesinin etkisi analiz

edilmiştir. Grup içi paraziti azaltmak için sayısal ön kodlama gerçekleştirilirken, öz bazlı ön hüzme oluşturma, grup içi paraziti ortadan kaldırmak ya da etkisiz hale getirmek için kullanılmıştır. Kullanıcı gruplamasında, Ağırlıklı Olabilirlik (WLD) ile K-ortalama kümeleme yaklaşımları benimsenmiştir. İki farklı çizelgeleme yöntemi ile yeniden çizelgelemenin sistem toplam hızına etkisi: Yarı-ortogonal Kullanıcı Seçimi (SUS) ve açgözlü/hırslı algoritmalar araştırılmış ve karşılaştırılmıştır. Simülasyon sonuçlarına dayanarak, her bir şema için yeniden zamanlama gerekliliğine ilişkin önemli bilgiler elde edilmiştir.

Dördüncül olarak, masif bir (MISO) sisteminde Derin Öğrenmeye (DL) dayalı, düşük hesaplama karmaşıklığı olan bir analog hüzmeleme tasarımı önerilmiştir. Önerilen hüzmeleme tasarımı, Evrişimli Sinir Ağı (CNN) modeline dayanmaktadır ve amaç, dene-timsiz öğrenme yoluyla toplam SE'yi maksimize etmektir. Ağın girişi, karmaşık değerli bir kanal katsayısıdır, ve bu nedenle, Hızlı Fourier Dönüşümü (FFT), Genlik ve Faz (A/Φ) ve Eş Fazlı ve Dörtlü (IQ) gibi farklı giriş veri gösterimleri gerçek değerlerin ayrıştırılması için kullanılmıştır. Önerilen ağ, geleneksel hüzmeleme yöntemleri ve Tam Bağlantılı (FC) Hüzme Oluşturan Sinir Ağı (BFNN) ile SE ve Kayan Nokta İşlemlerinin (FLOP'lar) karmaşıklığı açısından karşılaştırılmıştır.

Beşincil olarak, adil kullanıcı durumunu göz önünde bulundurarak, bir kısmi-NOMA (PNOMA) sisteminde güç ve örtüşme oranı (OR) için ortak tahsis algoritması önerilmiştir. PNOMA, sistem spektral verimliliğini artırabilen ve kullanıcı eşitliğini sağlayabilen geleceğin ve gelecek için ümit vadeden bir Çoklu Erişim (MA) tekniği olduğundan, pratikte verimli uygulama için mevcut ortak güç ve OR tahsisinin karmaşıklığı sorununun üstesinden gelmesi gerekmektedir. Bu nedenle, burada, Jain Endeksi ile ölçülen arzu edilen bir kullanıcı kullanım eşitliği sağlanarak, sistemin toplam veri hızının maksimize edildiği düşük karmaşıklıklı bir gradyan arama yaklaşımı benimsenmiştir. Simülasyon sonuçları, önerilen arama algoritmasının, aynı toplam oran performansına sahip kapsamlı aramaya kıyasla çok daha düşük hesaplama karmaşıklığı sağladığını ortaya koymuştur.

Altıncıl olarak, bir mmWave kanalında yine gelecek için ümit vaat eden NOMA çerçevesi önerilmiştir; burada PNOMA, geliştirilmiş SE için her kullanıcı grubunda benimsenirken, yakın konumdaki kullanıcılara, örtüşen bir iletim hüzmesinden hizmet sunulması öngörülmektedir. Üst üste binen hüzme kullanıcılarını gruplamak için bulanık kümeleme kullanılmıştır. Burada, kanal kazanç farkı ve bulanık üyelik bazlı kullanıcı eşleştirme algoritması önerilmiştir. Benzetim sonuçlarından, kullanıcıların toplam veri hızı performansını etkileyen Örtüşen Işın Oranının (OBR) önemi tartışılmıştır. Önerilen çerçevenin, geleneksel NOMA'ya kıyasla üst üste binen hüzme girişimi sorununu çözmeyi sağladığı ve spektral verimliliği arttırdığı gösterilmiştir.

Son olarak, Koordineli Çok Noktalı (CoMP) ağdaki NOMA'nın kusurlu kod çözme sorunu, ağda Yeniden Yapılandırılabilir Akıllı Yüzey (SIC) uygulanarak giderilmeye çalışılmıştır. İki hücre sınırındaki kullanıcının benzer bir kanal kazancına sahip olduğu ve yanlış kanal kazanç sırası ile kusurlu kod çözme nedeniyle Sinyal-Girişim-artı-Gürültü Oranlarının (SINR'ler) azalmasıyla sonuçlanan pratik bir çok hücreli senaryo düşünülmüştür. Bu nedenle, hücre ucu kullanıcılarının kanal kazancını ayırt etmek için, her hücrede daha düşük güç tahsisine sahip hücre ucu kullanıcısının yanında bir RIS kullanılır. Her kullanıcının SE'si için analitik Kesinti Olasılığı (OP) ifadeleri, ilgili kanal istatistiklerine dayalı olarak türetilir ve simülasyon sonuçlarıyla karşılaştırılarak bunların birbirleri ile uyduğu gösterilmiştir.

DoA tahmini, hüzme şekillendirme ve NOMA ile ilgili performans artırıcı analizlerden ve önerilen algoritmalarından ve sistemlerden, tez çalışmasının, 5G ve ötesi iletişim sistemlerindeki temel hususlar olan hesaplama karmaşıklığı ve spektral verimlilik ile ilgili sorunlara başarımı yüksek yaklaşımlar ortaya koyduğu gösterilmiştir.



Anahtar sözcükler: 5G, dizisel sinyal işleme, hüzmeleme, koordineli çoklu noktalar (CoMP), varış yönü (DoA), derin öğrenme, MIMO, MISO, karşılıklı bağlaşım (MC), ortogonal olmayan çoklu erişim (NOMA), güç tahsisi, yeniden yapılandırılabilir akıllı yüzey (RIS), spektral verimlilik (SE), kullanıcı kümeleme, kullanıcı eşleştirme..

ARRAY PROCESSING AND OPTIMIZATION TECHNIQUES OF BEAMFORMING AND RESOURCE ALLOCATION FOR ENHANCED SPECTRAL EFFICIENCY IN 5G AND BEYOND SYSTEMS

ABSTRACT

Nann Win Moe Thet

Ph.D. in Electrical, Electronics Engineering and Cyber Systems

Advisor: Assoc. Prof. Dr. Mehmet Kemal Özdemir

21 June 2021

Fifth Generation (5G) and beyond communication systems are regarded to be favourable technologies for the rapid rise of wireless data traffic demand, faster data transmission, and massive device connectivity. Array signal processing plays an important role in beamforming and Direction-of-Arrival (DoA) estimation in 5G and beyond wireless networks due to the deployment of large-scale antenna systems. While an increase in the number of antennae has the advantage of a high data rate, the cost and computational complexity of deployment are eventually increased. Therefore, this thesis addresses the complexity issues along with challenges to achieve a high data rate in a given bandwidth for 5G and beyond systems. Essentially, this thesis focuses on three main aspects of 5G systems: DoA estimation, beamforming, and Non-Orthogonal Multiple Access (NOMA), with their related problems of complexity and spectral efficiency (SE).

This thesis first presents a reduced-rank DoA estimation with unknown mutual coupling (MC) in Uniform Linear Array (ULA) antenna structure for coherent signals. The proposed method is based on Joint Iterative Subspace Optimization (JIO) and Minimum Variance (MV)-based MC auto-calibration, and the coherent signals are decorrelated by integrating Forward Backward Spatial Smoothing (FBSS) with the JIO process. The accuracy of the proposed method was analyzed in terms of root mean square error, success probability, and the complexity comparison was performed based on Central Processing Unit (CPU) run time.

Second, mutual coupling effect on the achievable sum-rate of the NOMA system is examined. The beam patterns and system sum-rate using different antenna configurations at the base station (BS) such as ULA, 2-Dimensional (2D) Uniform Circular Array (UCA), and staggered 3-Dimensional (3D) UCA are analyzed. Mutual coupling expressions based on Electromotive Force (EMF) for different antenna structures are also presented. Both uplink (UL) and downlink (DL) transmissions are performed and the respective sum-rate performances with and without MC compensation are investigated.

Third, the impact of user grouping and scheduling in Frequency Division Duplex (FDD) massive MIMO systems with fast fading channel is analyzed. Eigen-based pre-beamforming is utilized to cancel the inter-group interference while digital precoding is used to mitigate the intra-group interference. As for user grouping, K-mean clustering with Weighted Likelihood (WLD) is implemented. The effect of rescheduling on the system

sum-rate with two different scheduling methods: Semi-orthogonal User Selection (SUS) and greedy algorithms are investigated and compared. Significant insights on the requirement of rescheduling for each scheme are concluded based on the simulation results.

Fourth, a low computational complexity analog beamforming design based on Deep Learning (DL) in a massive MISO system is proposed. The proposed beamforming design is based on the Convolutional Neural Network (CNN) and the objective is to maximize the total SE by unsupervised learning. The input of the network is a complex-valued channel coefficient, thus, different types of input data representations such as Fast Fourier Transform (FFT), Amplitude and Phase (A/ Φ), and In-phase and Quadrature (IQ) were exploited for real values decomposition. The proposed network is compared with the traditional beamforming methods and the Fully-Connected (FC) Beamforming Neural Network (BFNN) in terms of SE and complexity of Floating-Point Operations (FLOPs).

Fifth, considering user fairness, a joint allocation algorithm for power and overlapping ratio (OR) in a partial-NOMA (PNOMA) system is proposed. Since PNOMA is a promising Multiple Access (MA) technique that can improve system spectral efficiency and provide user fairness, it is important to tackle the complexity issue of the current joint power and OR allocation for efficient implementation in practice. Therefore, a low-complexity gradient search approach is adopted here, in which the system sum-rate is maximized by satisfying a desired user fairness measured by Jain's Index. Simulation results conclude that the proposed search algorithm provides much lower computational complexity compared to the exhaustive search with the same sum-rate performance.

Sixth, a new promising NOMA framework in a mmWave channel is proposed, in which PNOMA is adopted in each user group for improved SE while closely located users are served in an overlapped transmit beam. Fuzzy clustering is employed to group the users in the overlapped beam. User pairing algorithm based on channel gain difference and fuzzy membership is proposed. The importance of Overlapping Beam Ratio (OBR) that affects the sum-rate performance of the users is discussed from the simulated results. It is demonstrated that the proposed framework enables to address the challenge of overlapped beam interference and enhances spectral efficiency compared to the traditional NOMA.

Lastly, the issue with imperfect decoding of NOMA in Coordinated Multi-points (CoMP) network is addressed by implementing Reconfigurable Intelligent Surface (RIS) in a network. A practical multi-cell scenario is considered, in which two cell-edge users have a similar channel gain, resulting in reduced Signal-to-Interference-plus-Noise Ratios (SINRs) due to imperfect decoding with the wrong channel gain order. Therefore, in order to distinguish the channel gain of the cell-edge users, a RIS is employed near the cell-edge user that has lower power allocation in each cell. Analytical Outage Probability (OP) expressions for the SE of each user are derived based on their respective channel statistics and compared with the simulation results to observe their agreement.

It can be seen from the performance analysis and proposed algorithms and systems related to DoA estimation, beamforming, and NOMA that the thesis work successfully tackles the issues with computational complexity and spectral efficiency, which are essential requirements in 5G and beyond communication systems.

Keywords: 5G, array signal processing, beamforming, coordinated multi-points (CoMP), direction-of-arrival (DoA), deep learning, MIMO, MISO, mutual coupling (MC), non-orthogonal multiple access (NOMA), power allocation, reconfigurable intelligent surface (RIS), spectral efficiency (SE), user clustering, user pairing.

CHAPTER 1

1. INTRODUCTION

1.1. Background

Rapid demands of high data rate traffic and faster data transmission have driven the need to develop the Fifth-Generation (5G) and beyond technologies. One of the driving factors for 5G and beyond systems is the array signal processing, which has been utilized successfully in many other applications such as sonar, radar, and wireless communication networks over the past decades. Array signal processing typically requires DoA estimation [1]. For the upcoming 5G and beyond systems, it is expected that array signal processing will play a big role when massive MIMO systems are deployed.

Current Fourth-Generation (4G) communication standard and structure cannot cope with the demand of 5G systems, which requires very high throughput connection, up to 10 Gbps; very high Spectral Efficiency (SE); very low latency, up to 1 ms; massive connectivity; and 10 to 100 higher number of connected UT than the current 4G technology [2]. Since throughput (capacity) of a wireless communication system is linearly related to SE and transmission bandwidth, increasing one or both of them results in an increased throughput. However, spectrum, as well as the transmit power, are a very scarce and limited resource in wireless communication. Efficient utilization of the available frequency band is a challenging task to accommodate the increasing number of connected UTs and their demands. In addition, complexity and power constraints make the development of next generation wireless communication systems more difficult.

Massive MIMO systems with beamforming is one of the key technologies in upcoming 5G systems. The purpose of beamforming is to increase the received signal power at a target receiver while cancelling or minimizing the target's signal power arriving at other

receivers. At the transmitter, beamforming is considered as a precoding technique, which generates a beam pattern with high gain toward a desired receiver, either UTs in downlink or BS in uplink. At a receiver, beamforming acts as a combiner, where the arriving signals from a desired source are constructively added and signals from other sources are nullified.

Millimeter Wave (mmWave) massive MIMO communications operating in the 28-300 GHz range has been considered as a prominent solution that can satisfy the large bandwidth and high data rate requirement of the next generation 5G and beyond communication networks [3], [4]. Although mmWave transmission suffers from significant Path-Loss (PL) in free space due to the small wavelength of the transmitted signals, the ability to employ large-scale antenna array tends to compensate the propagation losses by providing high beamforming gains resulting from spatial diversity of MIMO systems [3]. With the increasing demand of a growing number of users in the next generation wireless systems, MU massive MIMO have become a promising technology that can serve a large number of simultaneous users. Serving a great number of users simultaneously by massive MIMO can indeed increase the system capacity if beamforming methods are carefully designed such that the interference among the users is effectively suppressed.

In addition, it is known that mmWave MIMO systems are anticipated to operate on wideband channels with frequency selectivity [4]. Therefore, it is essential to exploit multiple access technologies that support wideband systems in order to enhance the system capacity. Orthogonal Frequency-Division Multiple Access (OFDMA) and NOMA are the popular multiple access technologies, which are employed in wideband MU MIMO systems. OFDMA has been around for quite some time and implemented in 4G systems. Since spectrum is a limited resource and it is also expensive to use more spectrum to increase the system throughput, NOMA was introduced to increase the system capacity without requiring to increase the spectral bandwidth [5]. NOMA scheme is enabled by two important techniques: superimposing the signals with proper power allocation at the transmitter and Successive Interference Cancellation (SIC) decoding at the receivers [6], [7]. NOMA has been regarded by many as a promising multiple access technology for 5G and beyond systems [5], [8], [9].

1.2. Motivation And Thesis Contributions

Direction of arrival estimation of multiple narrow-band signals has been extensively studied in the field of radar and sonar communications for civilian and military purposes. In recent years, the attention has been extended into cellular systems such as 4G/Long-Term Evolution (LTE) communications and mmWave communications for 5G and beyond technologies. Especially in 5G systems where massive number of antennae are being utilized, advanced beamforming techniques are employed at the BSs in order to provide services to many users simultaneously [10]–[12]. With the knowledge of direction of the incoming signals, BSs perform adaptive beamforming by steering transmitted beams toward desired users, while minimizing the undesired users' interference. Overall, systems with much higher capacity than the existing systems are anticipated.

For 5G and beyond systems, multiple antennas in the order of hundreds are proposed in order to compensate for the path loss of high frequency carriers. This technique is termed as massive MIMO [13], [14]. The use of many closely packed antennas, however, introduces mutual coupling between the antenna elements [15], [16]. With multiple directional beams targeting different user groups in massive MIMO 5G systems, accurate estimation of DoA of the incoming signals becomes an important task especially in the presence of Mutual Coupling (MC), as even small DoA estimation errors decrease the signal to Signal-to-Interference-plus-Noise Ratio (SINR), reducing the system capacity [17].

Thus, under the presence of mutual coupling, it is important to estimate the DoA correctly first to identify the desired user direction and then perform beamforming, which can transmit maximum power toward the direction of interest with lower interference [18]. The combination of DoA estimation and beamforming in MIMO systems results in better quality transmission links with higher spatial efficiency. Recently, researchers have been paying attention to NOMA, integrated with mmWave massive MIMO systems, due to the fact that NOMA can support more users and achieve higher performance compared to Orthogonal Multiple Access (OMA) technologies such as OFDMA under certain conditions. Unlike OMA, the same resources such as time, frequency, space, and code, are shared among multiple users with different power levels. This is then supported with SIC at the receivers [5]. Compared to traditional mmWave MIMO systems, which allow one beam to accommodate only one user for a given channel bandwidth, incorporation

of NOMA with mmWave systems allows multiple users to share the same beam and the channel bandwidth to enhance the spectral efficiency [19]–[22].

Due to the above-mentioned reasons, it can be clearly stated that DoA estimation, beamforming, and NOMA are the main aspects of upcoming 5G and beyond technologies to enable high capacity performance services. Thus, this thesis work focuses on analyzing and developing optimization techniques for the aforementioned technologies in order to improve 5G and beyond systems. The major objective of this thesis is to propose solutions that can satisfy the very high performance requirements such as reduced computational complexity and spectral efficiency by effectively integrating the emerging technologies that enhance the system performance. Specifically, the works in this thesis first tackle the high complexity problem of DoA estimation in massive MIMO systems with mutual coupling. Then, user scheduling effect and low complexity beamforming design for massive MIMO are investigated. The last parts of the thesis focus on spectral efficiency enhancement based on NOMA and recent emerging technologies such as RIS and Coordinated Multi-Points (CoMP). The detailed motivations and the contributions of this thesis are further elaborated in the following subsections.

1.2.1. Reduced-rank joint estimation of DoA with mutual coupling

The accuracy of the DoA estimation methods depends on the array size and the number of data available. Higher antenna array size and higher data samples offer better estimation performance at the price of higher computational cost. Most of the high-resolution methods consider the signals to be non-coherent and the array manifold to be perfectly known. However, wireless channels include multipath propagation, resulting in highly correlated or coherent signals, which then cause the high-resolution of DoA estimation techniques to degrade [23]–[25]. This is a major problem for the upcoming 5G systems, where massive MIMO systems are to be deployed for spatial multiplexing. Moreover, the array manifold is usually affected by the electromagnetic interaction between the antenna elements such as mutual coupling, which adversely affects the estimation accuracy [26]. Auto-calibration methods have been proposed in the literature to estimate the mutual coupling coefficients, however, these methods cause higher complexity for the case of massive MIMO systems due to an iterative process.

Therefore, in **Section 3.1**, a low complexity algorithm in joint estimation of DoAs and MC

for coherent signals is proposed. The proposed method is based on the Joint Iterative Optimization (JIO) and mutual coupling auto-calibration algorithm. Given an initial coupling vector, reduced-rank correlation matrix is estimated with the JIO approach, followed by iterative joint estimation of DoA and coupling with an auto-calibration algorithm based on the Capon's minimum variance criterion. The forward/backward spatial smoothing is employed to decorrelate the coherent signals in the process of rank reduction before the auto-calibration of mutual coupling. Performance of the proposed method is compared with the state of the art algorithms in terms of DoA Root-Mean-Square-Error (RMSE) and probability of successful estimation. It is shown that the proposed method has a similar performance as the state of the art auto-calibration methods while offering a lower computational complexity. This study was published in Wiley Transactions on Emerging Telecommunications Technologies [27].

1.2.2. Impact of mutual coupling on power-domain non-orthogonal multiple access (NOMA)

Compared to OMA technology, in power-domain NOMA, multiple users can be served at the same frequency and time, using different allocated power levels at the users. This then provides higher spectral efficiency and more number of users [5], [6]. This distinctive characteristic of NOMA is achieved by employing SIC technique, which was first introduced in [28]. By exploiting the degree of freedom in spatial-domain in addition to the advantage of NOMA, groups of users can be supported by NOMA spatially in different beams [29], [30]. However, in practical transmission, MC between antenna array elements causes performance degradation of the overall system such as changes in the radiation pattern, input impedance, gain, and bandwidth. Moreover, there exists a system sum-rate degradation if a properly compensated beamforming is not adopted [31], [32].

It is observed that the study on the mutual coupling formulation specifically in 3-D UCA structure, where several UCAs with different radii are placed above each other, is still limited. Moreover, to the best of our knowledge, there is no existing study in the literature that focuses on the mutual coupling effect in multi-antenna NOMA systems. Therefore, **Section 3.2** investigates the impact of mutual coupling on the achievable sum-rate of power-domain NOMA system in both UL and DL transmissions. We assume a single-antenna

user NOMA system with directional beamforming in the millimeter wave (mmW) channel. Due to mutual coupling effect at the BSs, the steering vector of the channel is affected. Consequently, this leads to distorted antenna patterns pointing towards different directions and reduction in channel gain, based on antenna array structure. In this work, different antenna geometries and configurations, such as 1-Dimension (1-D) ULA, 2-Dimensional (2-D), and 3-D UCA, are implemented at the BS, where induced electromotive force (EMF) and method of moment (MOM) techniques are used to generate the MC coefficients. We first examine the antenna patterns affected by MC, followed by channel gains of UTs. Then the sum-rate of the NOMA system is modified in the presence of MC. Furthermore, mutual coupling is compensated successfully for both UL and DL systems for the given antenna structures. Simulation results show that mutual coupling degrades the sum-rate performance of the NOMA system in all three array structures, especially in the UCA structure due to the smaller spacing of the array element in a circular shape, resulting in symmetric mutual coupling from both sides of the circle. On the other hand, it is also shown that compensating the mutual coupling effect by the MOM technique in the case of unknown MC or matrix inversion in the case of known MC significantly improves the system sum-rate in all scenarios. This study was published in IEEE ACCESS [33].

1.2.3. Performance analysis of user scheduling in massive MIMO with fast moving users

It is essential to acquire Channel State Information (CSI) at a BSs for all the active users in order to design the precoding matrix. In Frequency Division Duplex (FDD) systems, the BS sends downlink pilot symbols to the users so that the users can estimate their downlink channel. The estimated CSI is then sent back to the BS via an uplink channel. It is not efficient to acquire CSI at the BS since pilot overhead increases with the number of BS antennas, especially in mmWave transmission [34]. Moreover, the uplink feedback resource blocks also increase as the number of users increases. Thus, it is difficult to serve a large number of users simultaneously [35]. For wireless systems, user scheduling is an essential task for system fairness. However, in these systems, users typically move in and out of the transmission range of BSs. These mobile users experience a Doppler channel, which then adversely affects the system performance. Therefore, user scheduling must be updated from time to time in order to adapt the time-varying channel due to the mobility.

Section 3.3 analyzes the effect of the fast fading Doppler channel on user scheduling algorithms. Considering a mmWave downlink massive MIMO system, a two-stage precoding method is adopted to cancel the interference from users. Improved K-mean clustering method with Weighted Likelihood (WLD) similarity measure is employed to group the active users within a given region. After grouping the users, different scheduling methods, Semi-orthogonal User Selection (SUS) algorithm and greedy algorithm, are implemented. Initially, grouping and scheduling are performed based on the static channels. Then, the scheduled users are simultaneously served for the next time frames without rescheduling while the users are moving. With this approach, this work reveals how static and time-varying user grouping and scheduling methods perform in terms of system sum-rate when the fast moving users experience the Doppler effect. Different scenarios of number of active users and time frames are simulated. It is observed that rescheduling is required when the greedy algorithm is used in order to maintain a high sum-rate, while the SUS algorithm does not achieve high sum-rate compared to greedy algorithm. This study was published in the proceedings of PIMRC 2019 conference [36].

1.2.4. Low-complexity deep learning-based beamforming in MISO systems

The problem of determining an optimal beamforming design is a critical issue in the 5G and beyond wireless communication networks in order to be able to provide much higher data rate and faster data transmission. Although Digital Beamforming (DB) can provide high SE, it suffers from high power consumption and cost due to utilization of many Radio-Frequency (RF) chains. Thus, Hybrid Beamforming (HB) was proposed to reduce the hardware cost and power consumption while realizing close to optimal SE as DB [37]. Conventional HB approaches based on Orthogonal Matching Pursuit (OMP), Manifold Optimization (MO), and Alternating Minimization Algorithm using Phase Extraction (PE-Alt) are highly applied algorithms to tackle the problem of analog Phase Shifters (PSs) constant modulus constraint [37]–[39]. However, these conventional beamforming approaches are complicated due to the non-convex optimization problem of beamforming vectors with Analog Beamforming (AB) constant modulus constraint [38]. By using DL-based beamforming, it is possible to implement the optimization of beamforming in a real-time communication since the trained parameters are reserved after offline training.

Motivated by this, **Section 3.4** proposes a low-complexity deep learning-based BFNN for

massive MISO systems. An unsupervised learning-based Convolutional Neural Network (CNN) model is adopted. The network is trained to obtain an analog PSs-based beamforming vector of a given user by maximizing the system SE while maintaining the transmitted power constraint. The CSI for mmWave channel and SNR are used as input to the network. We also proposed a novel input feeding arrangement to the network and assessed its performance by using different input data representations. Simulation results show that the CNN-BFNN has the lowest complexity compared to a fully connected neural network (FCNN) and the existing conventional algorithms. Furthermore, the CNN model with Fast Fourier Transform (FFT) input provides the highest SE performance among all other input data representations. This study is accepted to be published in the proceedings of SIU 2021 conference [40].

1.2.5. Joint overlap ratios and power allocation with user fairness in partial non-orthogonal multiple access (PNOMA)

Power-domain NOMA technique allows multiple users to transmit many data streams simultaneously at the same frequency (subcarrier) and time using different power levels. At the receiver, SIC technique is performed to decode the received signal at respective UT. However, user interference occurs if SIC at the receiver is not performed perfectly. To reduce the amount of interference among NOMA users, recently an alternative approach called P-NOMA was proposed. In this approach, the system allows partially overlapped bandwidth of the users and enables them to use NOMA in the overlapped region while the users in the non-overlapped bandwidth are arranged to utilize OMA. What should be the amount of ORs and the corresponding power levels still needs further research.

Motivated by this, in **Section 3.5**, an algorithm for joint allocation of ORs and power in P-NOMA system is proposed. The proposed algorithm is based on gradient search, with the maximum sum-rate objective and user fairness constraint. Simulation results show that the proposed algorithm, which has lesser complexity than exhaustive search, obtains the optimum ORs and power allocation coefficient such that the maximum sum-rate of the P-NOMA is higher than that of the conventional NOMA while the target Jain's index fairness is achieved. This study was published in the proceedings of SIU 2020 conference [41].

1.2.6. Partial-beam non-orthogonal multiple access (PB-NOMA) with fuzzy clustering

With the integration of mmWave and NOMA, inter-group interference can be minimized by beamforming, while intra-group interference within the same group can be mitigated with NOMA scheme by taking the advantage of SIC technique [6]. Many researchers currently explore and propose novel techniques, including state of the art machine learning-based approaches, for resource allocation, user clustering and user pairing in mmWave-NOMA [42]–[45]. Besides traditional NOMA, hybrid NOMA systems, which can improve the achievable sum-rate by dynamically allocating NOMA and OMA at different subcarriers, or by controlling the usage of the allocated resource, have been explored [46], [47]. It can, however, be observed that there is a gap between the unconventional mmWave-NOMA systems and the machine learning-based clustering. Moreover, in a scenario, where users are closely located, there exists overlapped users between the groups, which cause higher inter-group interference.

Motivated by the above reasons, **Section 3.6** proposes a PB-NOMA system for mmWave channels, where the UTs partially belong to different user groups and power-domain P-NOMA technique is exploited in their allocated spectrum. While an individual beam serves the UTs in one group, the UTs in the same group, including the overlapped beam UTs, employ the P-NOMA scheme. Overlapped beam UTs are present when two near UTs are closely correlated and when they are equally belonging to two user groups. Fuzzy C-means (FCM) clustering method, which considers the channel correlation coefficient as a similarity measure, is proposed to group the users. Then, user pairing is performed based on the channel gain differences and fuzzy membership values. Simulation results reveal that the sum-rate performance of the proposed PB-NOMA scheme with fuzzy clustering is shown to be better than that of the conventional P-NOMA systems by adjusting OBR and lower Near UT's Overlap Ratio (NOR) in a preferable group. This study was published in IEEE Wireless Communication Letter [48].

1.2.7. Outage probability analysis of reconfigurable intelligent surface-enabled coordinated multi-points NOMA networks

In **Section 3.7**, an application of RIS in CoMP-NOMA system is investigated to enhance the received SNR of a cell-edge UT. In the proposed system, the case where two common

cell-edge UTs and a cell-center UT in every cell are considered. The cell-edge UTs are JT-CoMP users, which receive the signals from the two BSs of the edge. These users are located at the same distance from the BSs, thus their channel gains are not distinguishable for a successful SIC operation. In order to boost the channel gain of one of the cell-edge UTs, an additional path is created by employing a RIS in each cell. To evaluate the performance of the proposed network, the analytical Outage Probability (OP) expressions of the UTs are derived using the channel statistics of i) traditional JT-CoMP NOMA system, ii) JT-CoMP NOMA system with reflected path, and iii) JT-CoMP NOMA system with both direct and reflected paths. The analytical results in these scenarios are compared with the simulation results for validation and an upper-bound OP is also presented as a baseline. The numerical results reveal that the outage performance of the proposed network with RISs at both paths outperforms that of the traditional JT-CoMP NOMA scheme. This work was submitted to IEEE Transactions on Vehicular Technology [49].

CHAPTER 2

2. THEORETICAL PART

In this chapter, theoretical background and the related research of the scope of the work in this thesis are discussed.

2.1. Direction-of-Arrival (DoA) Estimation

Consider a ULA consisting of N_t antenna array elements, each equally spaced by d inter-element distance, it is assumed that M narrowband signals $\{s_m\}_{m=1}^M$ arrive from different angles $\{\theta_m\}_{m=1}^M$ at the ULA array, as depicted in **Figure 2.1**. Assuming that the steering

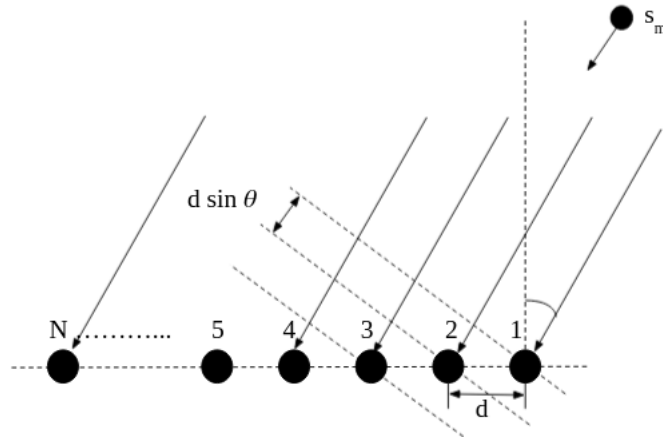


Figure 2.1: A uniform linear arrays system model.

vectors of the sources are not perfectly known due to MC, the resulting complex vector of the array output $\mathbf{x}(k) \in \mathbb{C}^{N_t \times 1}$ at k^{th} snapshot can be modeled as

$$\mathbf{x}(k) = \mathbf{C} \mathbf{A} \mathbf{s}(k) + \mathbf{n}(k) \quad k = 1, 2, \dots, K \quad (2.1)$$

where $\mathbf{s}(k) = [s_1(k), \dots, s_M(k)]^T \in \mathbb{C}^{M \times 1}$ and $\mathbf{n}(k) = [n_1(k), \dots, n_{N_t}(k)]^T \in \mathbb{C}^{N_t \times 1}$ are narrowband baseband signal and $n_m(k) \sim \mathcal{CN}(0, \sigma_k^2)$ being Additive White Gaussian Noise (AWGN) with zero-mean and σ_n^2 -variance, respectively. $\mathbf{A} = [\mathbf{a}(\theta_1), \dots, \mathbf{a}(\theta_M)] \in \mathbb{C}^{N_t \times M}$ represents the array manifold matrix, where $\mathbf{a}(\theta_m)$ is the steering vector and λ is the wavelength. $\mathbf{C} \in \mathbb{C}^{N_t \times N_t}$ is the Mutual Coupling Matrix (MCM), which is regarded to be direction-independent [50].

The signals arriving at the antenna array are assumed to be coherent such that all the received signals $\{s_m\}_{m=1}^M$ are attenuated and phase-delayed copies of the first signal, s_1 , i.e., $s_m(k) = b_m s_1(k)$, where b_m is a complex attenuation coefficient for the m^{th} signal. Assuming that the sources are uncorrelated with noise, the covariance matrix of $\mathbf{x}(k)$ is given by

$$\mathbf{R}_x = E[\mathbf{x}(k)\mathbf{x}^H(k)] = \mathbf{C}\mathbf{A}\mathbf{R}_s\mathbf{A}^H\mathbf{C}^H + \sigma_n^2\mathbf{I}_N \in \mathbb{C}^{N_t \times N_t} \quad (2.2)$$

where σ_n^2 is the noise variance, $E[\cdot]$ and $(\cdot)^H$ represent expectation and conjugate transpose operations, respectively. $\mathbf{R}_s = E[\mathbf{s}(k)\mathbf{s}^H(k)]$ is the signal covariance matrix, and $\mathbf{I}_N$ is an $N_t \times N_t$ identity matrix. When the signals are coherent, $\mathbf{R}_s$ becomes rank deficient. $\mathbf{R}_s$ can be further expressed as [24]

$$\mathbf{R}_s = E[\mathbf{s}(k)\mathbf{s}^H(k)] = \mathbf{b}\mathbf{b}^H E[s_1(k)s_1^H(k)] \quad (2.3)$$

where $\mathbf{b} = [b_1, b_2, \dots, b_M]^T$ is an attenuation vector and $E[s_1(k)s_1^H(k)]$ is a constant corresponding to the variance of s_1 . It can be seen from (2.3) that the rank of $\mathbf{R}_s$ is one, or $r = 1$. This case, however, results in a matrix singularity, which ultimately leads to inaccurate estimates of DoA if conventional methods were to be used.

In DoA estimation, beamforming is implemented at the receiver in order to estimate the location of a source or a desired signal arriving at the antenna array. This is achieved by exploiting noise and Signal-Not-of-Interest (SNOI) from other directions [51]. There are three basic DoA estimation approaches: conventional beamformer, adaptive beamformer, and subspace based techniques.

2.1.1. Conventional beamformer

Delay-and-sum beamforming is known as a classical beamforming method. In time domain, the beamformer basically delays the incoming signals arriving at each antenna array

element by some time delays in order to compensate the arrival time differences of the incident signals at each array element. The delayed signals are then added to obtain the beamformer output [52]. In frequency domain, time delaying represents phase shifting, thus applying PSs vector, $\mathbf{w}$, on incoming signals at i^{th} sample, $\mathbf{x}(i)$, and summing them results in the beamformer output $y(i) = \mathbf{w}^H \mathbf{x}(i)$ [53]. In conventional beamformer, the PSs vector of the Uniform Linear Array (ULA) at phase θ , $\mathbf{w}(\theta)$, can be defined as a normalized array manifold or steering vector, $\mathbf{a}(\theta)$, as

$$\mathbf{w}(\theta) = \mathbf{a}(\theta) = \frac{1}{\sqrt{N_t}} \left[1, e^{-j \frac{2\pi d}{\lambda} \sin(\theta)}, \dots, e^{-j \frac{2\pi (N_t-1)d}{\lambda} \sin(\theta)} \right]^T.$$

The phase, which generates the maximum mean output power of the beamformer,

$$P(\theta) = E\{|y|^2\} = \mathbf{w}^H(\theta) E\{\mathbf{x}\mathbf{x}^H\} \mathbf{w}(\theta) = \mathbf{w}^H(\theta) \mathbf{R}_x \mathbf{w}(\theta)$$

is selected, and it steers the array beam toward the look direction (direction of Signal-Of-Interest (SOI)). The resulting mean power of the beamformer output is considered to be equivalent to the source power in the SOI direction [54]. It is worth noticing that the array with this type of beamforming is known as a phased array antenna.

2.1.2. Adaptive beamformer

In adaptive beamforming, the beamformer weights dynamically gets changed unlike the conventional beamformer, which has the constant weights regardless of the presence of interfering signals. The adaptive beamformer weights are obtained based on some objectives and constraints in order to cancel the interfering signals and steer the beam pattern toward the direction of SOI [55], [56]. Minimum Variance Distortionless Response (MVDR) or Capon's Minimum Variance DoA estimation is an adaptive beamforming method, where the weights are calculated by minimizing the output power of SNOI in all other directions while maintaining the unity gain in the direction of the desired signal [57], [58]. After solving the optimization problem of MVDR, the beamformer weight is obtained as [59]

$$\mathbf{w}(\theta) = \frac{\mathbf{R}_x^{-1} \mathbf{a}(\theta)}{\mathbf{a}^H(\theta) \mathbf{R}_x^{-1} \mathbf{a}(\theta)}, \quad (2.4)$$

where $\mathbf{R}_x$ is a covariance matrix of the incoming signal vector at the array elements. By using the weight and the resulting beamformer output, the maximum output power which indicates the desired DoA is obtained.

2.1.3. Subspace-based techniques

Multiple Signal Classification (MUSIC) algorithm [60] and the Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) [61] are the most popular and widely used subspace based DoA estimation techniques. In MUSIC, eigen-decomposition is utilized to divide the eigenvectors of the covariance matrix of the incoming signal; $\mathbf{R}_x$, into signal and noise subspaces. Then, by using the matrix consisting of the eigenvectors of noise subspace, $\mathbf{E}_n$, power spectrum of MUSIC algorithm is obtained as [60]

$$P(\theta) = \frac{1}{\mathbf{a}^H(\theta) \mathbf{E}_n \mathbf{E}_n^H \mathbf{a}(\theta)}. \quad (2.5)$$

The estimated DoAs can be extracted from the peaks of the power spectrum, which are formed by the orthogonality between $\mathbf{a}(\theta)$ and $\mathbf{E}_n$. Hence, ideally $\mathbf{a}^H(\theta) \mathbf{E}_n = 0$. Since maxima search process in MUSIC is to be performed, a method that has a better computational efficiency is proposed in [61], known as ESPRIT algorithm. This approach is based on the rotational invariance property of the signal subspace. Two subarrays of ULA are formed by leaving the first and last array element, respectively. Thus, the steering vectors of one subarray is related to that of the other by rotation matrix, $\Phi = \text{diag}\{\exp(-j(2\pi/\lambda)d \sin(\theta_1)), \dots, \exp(-j(2\pi/\lambda)d \sin(\theta_M))\}$. Similar to MUSIC, eigen vectors matrices of the signal subspace resulting from two subarrays, $\mathbf{E}_{s_1}$ and $\mathbf{E}_{s_2}$, are obtained. By using the eigenvector matrices and solving for M eigenvalues of the rotation matrix $\lambda_l \forall l = 1, \dots, M$, DoAs, θ_l , are directly calculated as [61]

$$\theta_l = \sin^{-1} \left(\frac{\arg(\lambda_l)}{kd} \right). \quad (2.6)$$

2.2. Mutual Coupling

With the rapid growth of the demand in wireless communications services and scarcity in the frequency spectrum, NOMA has been gaining attention over the past few years. In DL NOMA, the users with strong channel gain can perfectly cancel the interference from weak users using SIC before decoding its own signal [29], [62]. On the contrary, in UL NOMA, far users with the weak channel condition can remove the strong user interference via SIC since all users can utilize the maximum power available at them [30], [62]. The applications of mmWave communication have become the essential technology for 5G

and beyond wireless communications systems [63], [64]. Thus, many researchers have been paying attention to the research where NOMA system is integrated with multiple-antenna beamforming techniques in mmWave channel [19], [65]–[68]. However, in real transmission, the electromagnetic interaction between antenna array elements called MC can cause performance degradation of any system. Therefore, mutual coupling, which can be obtained using different estimation methods [27], [69]–[72], must be compensated to reduce its adverse effect on the system. In the case where MC coefficients cannot be estimated perfectly, different MC compensation techniques, which include invasive and non-invasive techniques, can be used to compensate for the performance degradation. However, invasive techniques result in higher system complexity due to physical modification of the antenna array structure [73].

2.2.1. Mutual coupling matrix (MCM) based on array configuration

As reported in the work of Friedlander and Weiss [50], the MC coefficient between any two equally spaced antenna elements is assumed to be the same. Moreover, it is also inversely related to the distance between the elements, and thus the MC coefficient will become approximately zero when any two elements are separated by several wavelengths.

The mutual coupling matrix, $\mathbf{C} \in \mathbb{C}^{N_t \times N_t}$ can be defined as [74], [75]

$$\mathbf{C} = (\mathbf{Z}_A + \mathbf{Z}_L)(\mathbf{Z} + \mathbf{Z}_L \mathbf{I}_N)^{-1}, \quad (2.7)$$

where Z_A is the self impedance (isolated impedance), which is $Z_A = (73 + j42.5) \Omega$ for half-wavelength dipole antenna with length $l = \lambda/2$, and $Z_L = 50 \Omega$ is the terminal impedance connected to each antenna element. $\mathbf{Z} \in \mathbb{C}^{N_t \times N_t}$ is the mutual impedance matrix of the array, where its diagonal elements are the same as the self impedance, $Z_{mn} = Z_A, \forall m = n$. The mutual impedance between m^{th} and n^{th} equal length half-wavelength dipole antennae can be written as $Z_{mn} = R_{mn} + jX_{mn}$, where R_{mn} and X_{mn} are the resistance and the reactance between the antenna elements. These two are defined according to the classical induced EMF approach, following side-by-side array configuration for ULA and 2-D UCA and parallel-in-echelon array configuration for 3-D UCA [56], [76], and they are varied with the horizontal distance between two antennae, d_{mn} . In UCA configuration, since the antennae are placed in the circular direction, the horizontal distance between two antennae is defined as a chord length of the circle between the m^{th} and

n^{th} antennae, $d_{mn} = 2r \sin(\phi_n/2)$.

Assuming array reciprocity, the transmit and receive mutual coupling matrices are equal as $\mathbf{C}_t = \mathbf{C}_r = \mathbf{C}$ [75]. Due to the fact that MC coefficients between equally spaced antenna elements are the same and inversely related to their distances [50], the mutual impedance matrix can be modeled using a symmetric Toeplitz matrix as

$$\mathbf{Z} = \text{Toeplitz}\{\mathbf{z}^T, \mathbf{z}^T\}, \quad (2.8)$$

where $\mathbf{z} = [z_1, z_2, \dots, z_{N_t}]^T \in \mathbb{C}^{N_t \times 1}$ is a complex vector composed of N_t mutual impedance values. A symmetric Toeplitz matrix for any vector $\mathbf{v} = [v_0, v_1, \dots, v_{L-1}]$ with length L is defined as,

$$\text{Toeplitz}\{\mathbf{v}\} = \begin{bmatrix} v_0 & v_1 & \dots & v_{L-1} \\ v_1 & v_2 & \dots & v_{L-2} \\ \vdots & \vdots & \ddots & \vdots \\ v_{L-1} & v_{L-2} & \dots & v_0 \end{bmatrix}. \quad (2.9)$$

In ULA, $\mathbf{z}$ can be formed by calculating Z_{1n} the mutual impedance among the first antenna and the rest of $n = 1, \dots, N_t$ antennae. Therefore, $\mathbf{C}$ can be modeled as a banded symmetric Toeplitz matrix or a diagonal-constant matrix, i.e., $\mathbf{C} = \text{Toeplitz}\{[\mathbf{c}^T, \mathbf{0}_{1 \times (N_t-L)}]\}$. Here, $\mathbf{c} = [c_0, c_1, c_2, \dots, c_{L-1}]^T \in \mathbb{C}^{L \times 1}$ is a complex vector consisting of L nonzero unique coupling coefficients.

On the other hand, due to the symmetric structure of a circle, $\mathbf{z}$ in UCA structure can be reduced to

$$\mathbf{z} = [z_1, \dots, z_L, z_{L-1}, \dots, z_3, z_2], \in \mathbb{C}^{N_t \times 1}, \quad (2.10)$$

for N_t being an even number with $L = \frac{N_t}{2} + 1$, and

$$\mathbf{z} = [z_1, \dots, z_L, z_L, \dots, z_3, z_2], \in \mathbb{C}^{N_t \times 1}, \quad (2.11)$$

for N_t being an odd number with $L = (N_t + 1)/2$. Thus, it is required to only calculate $L < N_t$ number of mutual impedance values in UCA.

In the case of staggered 3-D UCA as shown in **Figure 2.3**, the impedance matrix can be firstly written as a block diagonal matrix of the impedance matrix of the first and the second UCA without staggered configuration, $\mathbf{Z}_1$ and $\mathbf{Z}_2$, as $\mathbf{Z} = \text{blkdiag}(\mathbf{Z}_1, \mathbf{Z}_2)$. Then, the upper triangular matrix of $\mathbf{Z}$, which consists of the mutual impedance between

the antenna m of the first UCA and n of the second UCA in general, is defined by

$$\mathbf{Z}_u = \begin{bmatrix} Z_{1(N_1+1)} & Z_{1(N_1+2)} & \cdot & \cdot & Z_{1N_2} \\ Z_{2(N_1+1)} & Z_{2(N_1+2)} & \cdot & \cdot & Z_{2N_2} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ Z_{N_1(N_1+1)} & Z_{N_1(N_1+2)} & \cdot & \cdot & Z_{N_1N_2} \end{bmatrix}, \in \mathbb{C}^{N_1 \times N_2}, \quad (2.12)$$

where $Z_{mn}, \forall m = 1, 2, \dots, N_1$ and $\forall n = N_1 + 1, N_1 + 2, \dots, N_2$, is calculated using EMF closed form solution based on parallel-in-echelon array configuration [56] since they are placed in staggered arrangement. Likewise, the lower triangular matrices can be obtained as $\mathbf{Z}_l = \mathbf{Z}_u^T$. Therefore, the finalized $\mathbf{Z}$ for **Figure 2.3b** structure with $N_1 = 3, N_2 = 4, N_t = N_1 + N_2$, can be expressed by

$$\mathbf{Z}_u = \begin{bmatrix} \mathbf{Z}_1 & \mathbf{Z}_u \\ \mathbf{Z}_u^T & \mathbf{Z}_2 \end{bmatrix}, \in \mathbb{C}^{N_t \times N_t}. \quad (2.13)$$

2.3. Array Steering Vector

Consider a BS with 1-D ULA along the y-axis with inter-element spacing $d = \lambda/2$, the normalized steering vector with elevation angle fixed at $\theta_k = \pi/2$ and the first antenna element placed at the origin, is given by

$$\mathbf{a}_k(\phi_k, \theta_k) = \frac{1}{\sqrt{N_t}} e^{j\beta d n \sin \theta_k \sin \phi_k}, n = [0, \dots, N_t - 1]^T, \quad (2.14)$$

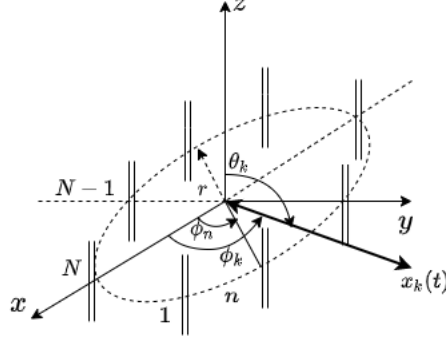
where $\beta = 2\pi/\lambda$, and signal of the k^{th} UT is transceived at the azimuth angles, $\phi_k \sim \mathcal{U}(-\pi, \pi)$. In case of a UCA with radius, r , which lies in the XY-plane as shown in **Figure 2.2**, the steering vector with $\theta_k = \pi/2$ can be written as

$$\mathbf{a}_k(\phi_k, \theta_k) = \frac{1}{\sqrt{N_t}} e^{j\beta r \sin \theta_k \cos(\phi_k - \phi_n)}, n = [1, \dots, N_t]^T, \quad (2.15)$$

where $\phi_n = 2\pi n/N_t$ is the angular position of the n antenna elements.

Another array geometry considered in this study is a staggered 3-D UCA array structure. As illustrated in **Figure 2.3**, the inner UCA (1^{st} circle) with the radius, r_1 , and the size, N_1 , is placed above the outer UCA (2^{nd} circle) with the radius, r_2 , and the size, N_2 , at $z = \lambda/4$ on the z-axis. The steering vector in this case can be obtained by concatenating the steering vectors of inner and outer UCA. The steering vector of the 1^{st} UCA for the

a)



b)

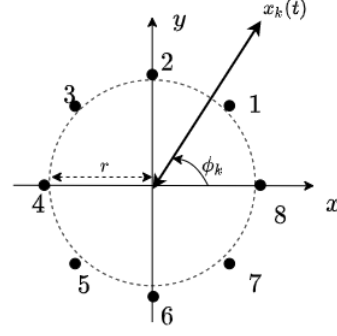
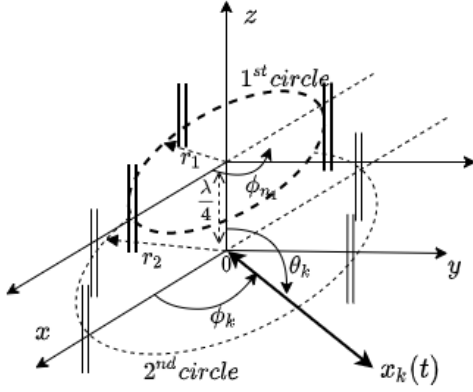


Figure 2.2: Uniform circular array geometry: **a)** 3-D view, **b)** Top view in XY-plane.

a)



b)

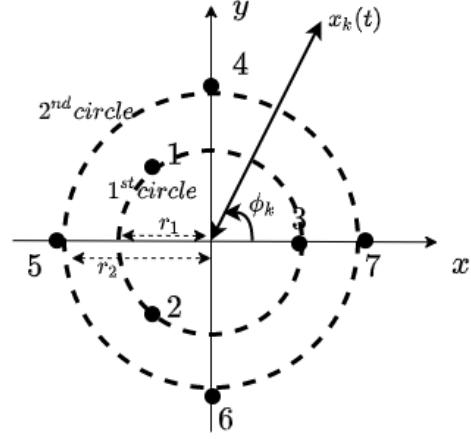


Figure 2.3: Uniform circular array geometry with staggered UCA at $z = \lambda/4$: **a)** 3-D view, **b)** Top view in XY-plane.

k^{th} UT is given as

$$\mathbf{a}_k^{(1)}(\phi_k, \theta_k) = \frac{1}{\sqrt{N_t}} e^{j\beta(r \sin \theta_k \cos(\phi_k - \phi_n) + z \cos \theta_k)}. \quad (2.16)$$

Considering $\theta_k = \pi/2$, (2.16) is reduced to the steering vector of non-staggered UCA as (2.15), and the steering vector of the 2nd UCA, $\mathbf{a}_k^{(2)}(\phi_k, \theta_k)$, is given as the same in (2.15). Without loss of generality, steering vector of 3-D UCA with N_c circles in general is written as

$$\mathbf{a}_k(\phi_k, \theta_k) = \left[\mathbf{a}_k^{(1)}(\phi_k, \theta_k)^T, \dots, \mathbf{a}_k^{(N_c)}(\phi_k, \theta_k)^T \right]^T. \quad (2.17)$$

It can be seen that the steering vector is largely based on the array geometries, number of array elements, and inter-element spacing.

2.4. Channel Model

Mathematically, mmWave channel vector between the BS antenna array and the k^{th} user is modeled as the geometric channel model composed of limited L scatterers for each user [38], [77], [78]. The UL mmWave channel vector between the BS and the k^{th} UT, is defined as

$$\mathbf{h}_{ULk} = \frac{\alpha}{PL_k} \sum_{l=1}^L \beta_{kl} \mathbf{a}_k(\phi_k^l, \theta_k^l) \in \mathbb{C}^{N_t \times 1}. \quad (2.18)$$

In the subsequent sections of this thesis, the subscripts “DL/UL” are omitted in the channel vector, and only use $\mathbf{h}_k = \mathbf{h}_{ULk}$ for the sake of readability. Here, $\alpha = \sqrt{N_t/KL}$ is a normalization factor to satisfy $\mathbb{E}[\|\mathbf{H}\|_F^2] = N_t K$, in which $\mathbf{H} = [\mathbf{h}_1, \dots, \mathbf{h}_K]$ if there are K UTs. $\beta_k \sim \mathcal{CN}(0, 1)$ denotes a zero-mean unit-variance complex channel fading coefficient of the l^{th} path for the k^{th} user. $PL_k = (4\pi/\lambda)^2 d_k^\eta$ is the PL between the BS and user k with the distance d_k and the PL exponent η , and $\mathbf{a}(\phi_k^l, \theta_k^l) \in \mathbb{C}^{N_t \times 1}$ is an antenna array steering vector, based on the array geometry such as ULA, UCA, etc. Both DoAs and Direction-of-Departures (DoDs) of the l path are usually distributed under Laplacian distribution with uniformly distributed mean angles μ_k and a constant angular spread σ_s [39]. Assuming a reciprocal channel, the DL channel vector between the UTs and the BS can be expressed as $\mathbf{h}_{DLk} = \mathbf{h}_{ULk}^H \in \mathbb{C}^{1 \times N_t}$.

2.5. Effective Steering Vector And Transmit Beam Power With MC

The effective steering vectors and the coupled channel vectors of the UT k in UL and DL transmissions, are respectively written by [31], [32], [79]

$$\hat{\mathbf{a}}_k^{UL}(\phi_k) = \mathbf{C} \mathbf{a}_k(\phi_k) \in \mathbb{C}^{N_t \times 1}, \quad (2.19)$$

$$\hat{\mathbf{a}}_k^{DL}(\phi_k) = (\mathbf{C} \mathbf{a}_k(\phi_k))^H = \mathbf{a}_k(\phi_k)^H \mathbf{C}^H \in \mathbb{C}^{1 \times N_t}, \quad (2.20)$$

$$\hat{\mathbf{h}}_k^{UL} = \mathbf{C} \mathbf{h}_k = \frac{\alpha}{PL_k} \sum_{l=1}^L \beta_{kl} \mathbf{C} \mathbf{a}_k(\phi_k) \in \mathbb{C}^{N_t \times 1}, \quad (2.21)$$

$$\hat{\mathbf{h}}_k^{DL} = (\mathbf{C} \mathbf{h}_k)^H = \frac{\alpha}{PL_k} \sum_{l=1}^L \beta_{kl} \mathbf{a}_k^H(\phi_k) \mathbf{C}^H \in \mathbb{C}^{1 \times N_t}, \quad (2.22)$$

Based on the effective steering vector, the transmitted beam power with the analog beam-forming towards the nearest UT is modified as (2.23), and the received beam power for

the k^{th} UT at the BS after post-coding is obtained as (2.24) as follows

$$\zeta_{MC}^{DL}(\phi_k) = |\mathbf{a}(\phi_k)^H \mathbf{C}^H \mathbf{v}|^2 = |\mathbf{a}(\phi_k)^H \mathbf{C}^H \mathbf{a}(\phi_1)|^2, \quad (2.23)$$

$$\zeta_{MC}^{UL}(\phi_k) = |\mathbf{f}^H \mathbf{C} \mathbf{a}(\phi_k)|^2 = |\mathbf{a}(\phi_1)^H \mathbf{C} \mathbf{a}(\phi_k)|^2. \quad (2.24)$$

where $\mathbf{v}$ and $\mathbf{f}$ are the normalized transmit and received beamforming vectors.

2.6. Beamforming

Beamforming is a signal processing method used in multiple antenna systems which creates antenna beam pattern. The radiation beams at either/both Transmitter (Tx) or Receiver (Rx) are created by constructively adding the SOI and attenuating the SNOI or interfering signals [51], [80].

The main purposes of a MIMO system is to increase the system capacity through spatial multiplexing [81], [82] and to improve the reliability of the communication link through spatial diversity [83]–[85]. Beamforming for spatial multiplexing is performed to maximize the received power at the target UT while minimizing the power that leaks to the other UTs.

At the transmitter, beamforming is considered as a precoding technique which generates a beam pattern with high gain toward the desired receiver either users in downlink transmission or base station in uplink transmission. At the receiver, beamforming acts as a combiner where the arriving signals from a desired source are constructively added and the signals from other sources are nullified. Thus, it is important to estimate the DOA correctly first to identify the desired user direction and then perform beamforming which can transmit maximum power toward the direction of interest with lower interference [18]. The combination of DOA estimation and beamforming in MIMO systems results in better quality transmission link with higher spectrum efficiency [86]. As depicted in **Figure 2.4**, there are three basic beamforming types: a) analog beamforming, b) digital beamforming and c) hybrid beamforming.

2.6.1. Analog beamforming

Analog beamforming is designed to control the phase of the incoming signal at the antenna array either at the transmitter or receiver. It is similar to delay-and-sum beamforming

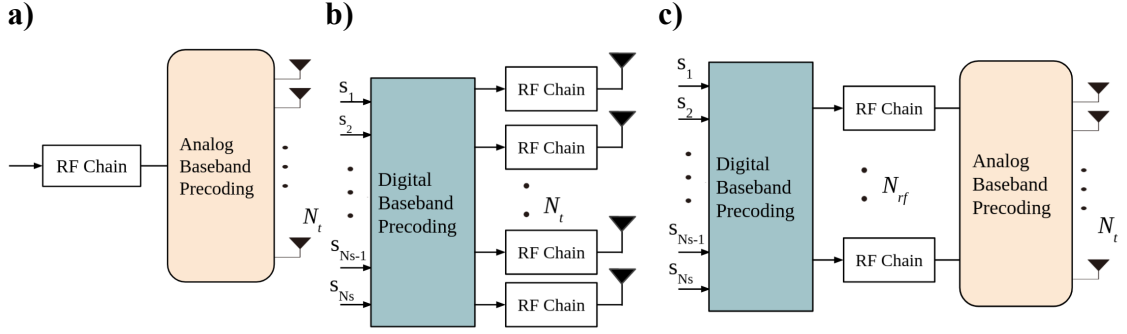


Figure 2.4: Beamforming structures for spatial multiplexing: **a)** analog beamforming, **b)** digital beamforming, **c)** hybrid beamforming.

for DOA estimation. Basically, the implementation of analog beamforming is performed via digitally controllable PSs and/or Variable Gain Amplifiers (VGAs) (amplifying the amplitude independently with the VGAs) [87], [88]. The authors in [89] have shown that cooperating phase-shifters and switches result in a much higher Energy Efficiency (EE). Conventionally, analog beamforming architecture includes one RF chain, which is composed of Digital-to-Analog-Converter (DAC) for Tx and Analog-to-Digital-Converter (ADC) for Rx, and one PSs for each antenna element as shown in **Figure 2.4a**.

There are two types of phase-shifters: namely infinite/high-resolution PSs and finite/low-resolution PSs. Infinite-resolution PSs provide better sum-rate performance close to the fully-digital beamforming due to the unlimited number of phase shifts [90]. However, the increase in resolution results in significantly higher power consumption and higher hardware complexity [91]. Therefore, low-resolution PSs, which have a finite set of phases, are implemented in practice even though they cannot provide a precise beam steering. The analog beamformer with B-bits-resolution PSs is given as $[\mathbf{V}]_{i,j} \in \mathcal{F}$, where $\mathcal{F} = \{e^{-j(2\pi b/2^B)}/\sqrt{N_t} \mid b = 0, 1, \dots, 2^B - 1\}$ [92].

At the transmitter side, a signal that passes through a single DAC is sent across the antenna array elements via PSs. Analog PSs are applied on the signal before the RF up-conversion or after the up-conversion in order to steer the beam toward the desired direction [93]. At the receiver side, it is a reverse process of the transmit beamforming. Each analog beamforming weights are assumed to have a constant modulus, which makes the use of low cost PSs possible [94], [95]. Since an analog beamformer requires only one RF chain, the power consumption is less and the hardware cost is low as well [96]. On the other hand, the greatest disadvantage of analog beamforming is that it only allow the phase

of the signal to be controlled, but not the amplitude. This however, leads to lower SE compared to digital beamforming [94]. Moreover, the analog beamformer can only serve one user at a time.

2.6.2. Digital beamforming

In digital beamforming, which is also known as precoding for beamforming with multiple data streams, the same number of RF chains as the number of antennas is required. Thus, different signals are fed to each antenna element as shown in **Figure 2.4b**, resulting in different powers and phases at each antenna to provide spatial multiplexing. Here, the complexity and power consumption are high due to the high number of RF chains. As can be deduced, digital beamforming can control both amplitude and phase of the transmitted signals while analog beamforming can change the phase using phase-shifter [97]. Digital beamforming is implemented in baseband domain using a digital processing unit, DAC/ADC, and mixers [96]. Generally, there are three types of digital beamforming, also known as linear precoders, which are widely used in the literature; 1) Zero-Forcing (ZF) precoder, 2) Maximum Ratio Transmission (MRT) or Matched Filter (MF), and 3) Minimum-Mean-Square-Error (MMSE)/Regularized ZF (RZF) precoder.

ZF precoder is designed to fully nullify MU interference by generating a beamforming vector which is orthogonal to the co-user channels [98]. Mathematically, pseudo-inverse of the channel matrix $\mathbf{H}$ is considered as a ZF precoder matrix as $\mathbf{D}^{ZF} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1}/\alpha$, where $\alpha = \sqrt{\|\mathbf{H}^H(\mathbf{H}\mathbf{H}^H)^{-1}\|_F^2/P_t}$ is a normalization for power constraint and $\|\cdot\|_F$ represents Frobenius norm of a matrix. Applying ZF precoder at BS, the effective channel matrix, $\hat{\mathbf{H}} = \mathbf{H}\mathbf{D}^{ZF}$ becomes a diagonal matrix since the off-diagonal elements, which correspond to user-interference channels, are all zeros. The ZF precoder has a better performance than MRT in the high SNR region while MRT outperforms ZF in the low SNR region [99]. Moreover, Zero-Forcing Beamforming (ZFB) is valid only when the number of users (only single-antenna users) is less than or equal to the number of transmit antennas. Its performance becomes constant and does not increase linearly with N_t as N_t goes to infinity [100].

The purpose of MRT beamforming is to construct a beamforming design which maximizes received SNR at the target user without considering the other users interference. Thus,

MRT precoder matrix is given as $\mathbf{D}^{MRT} = \mathbf{H}^H / \alpha$, where $\alpha = \sqrt{\|\mathbf{H}^H\|_F^2 / P_t}$. MRT precoding is preferable at the low SNR region, where the BS utilizes less transmit power, while its sum-rate performance is significantly less than ZF at the high SNR region [98].

Due to the poor performance of the ZF and MRT beamforming across different SNR values, a MMSE or regularized ZF precoder is proposed in [100]. In massive MIMO systems, MMSE/RZF precoder achieves near-optimal beamforming performance for all ranges of SNR region since it consists of the asymptotic properties of both MRT and ZF [98]. An identity matrix $\mathbf{I}$ with diagonal loading scale is added to the part of ZF before inversion, and RZF is expressed as $\mathbf{D}^{RZF} = \mathbf{H}^H (\mathbf{H} \mathbf{H}^H + \gamma \mathbf{I})^{-1} / \alpha$, where $\alpha = \sqrt{\|\mathbf{H}^H (\mathbf{H} \mathbf{H}^H + \gamma \mathbf{I})^{-1}\|_F^2 / P_t}$ and $\gamma > 0$ is the regularization factor. In uniform power distributed MIMO systems, the optimized γ , which achieves the maximum sum-rate, is obtained as $\gamma = K / P_t$ [100]. When $\gamma = 0$ and $\gamma \rightarrow \infty$, RZF precoder becomes ZF precoder and MRT precoder, respectively.

In practice, digital beamforming is not suitable for 5G implementation on mobile user equipment due to its hardware complexity and high power consumption and cost. However, since a BS can utilize much more power and cost, digital beamforming can be applied at the BS in order to benefit the multi data streams and simultaneous user transmissions.

2.6.3. Hybrid beamforming

In order to tackle the low SE problem of analog beamforming and high cost and power consumption problem of digital beamforming, hybrid analog and digital beamforming has been investigated [38], [101]–[103]. In HB, N_s data streams firstly pass through the digital baseband precoder, then the precoded N_{rf}^t signals are sent to the analog RF beamformer via $N_s \leq N_{rf}^t \leq N_t$ RF chains as shown in **Figure 2.4c** [96]. The aim of the analog beamformer is to increase the beamforming gains and obtain precise directional beams to compensate for the propagation loss by controlling the phases of the transmitted signals. On the other hand, the digital precoder is responsible in designing the transmitter for sending multiple data streams without users interfering with each other in single-user massive MIMO systems [38] and to cancel the interference from other users in MU massive MIMO systems [101] for higher system capacity performance [104], [105]. Therefore, HB offers

good characteristics of both analog and digital beamforming; having a low complex hardware, less power consumption, and better SE.

One of the advantages of HB is that the number of RF chains is less than the number of antennas but greater than the number of data streams. That makes HB an energy efficient beamforming scheme with the help of digital beamforming while employing a properly designed analog beamforming can achieve higher beamforming gain and diversity as the number of antennas increases [103].

There are many studies which have analyzed and designed different types of HB schemes and architectures. The main purpose of these HB design is to achieve a near-optimal performance, which is close to fully-digital beamforming performance, while reducing the power consumption and complexity. Most of the studies focus on solving the beamforming optimization problem that maximizes the system capacity with a constant modulus constraint for low-cost analog PSs and a maximum power $P_t = P_{max}$ constraint. The capacity of the system, which is related to SINR of the K number of users, is defined as

$$C = \sum_{k=1}^K \log_2(1 + \text{SINR}_k), \quad (2.25)$$

where

$$\text{SINR}_k = \frac{|\mathbf{h}_k^H \mathbf{b}_k \mathbf{p}_k|^2}{\sum_{i=1, i \neq k}^K |\mathbf{h}_k^H \mathbf{b}_k \mathbf{p}_i|^2 + \sigma_n^2} \quad (2.26)$$

and $\mathbf{B} = [\mathbf{b}_1, \dots, \mathbf{b}_r] \in \mathbb{C}^{N_t \times r}$ is an analog beamforming matrix and $\mathbf{P} = [\mathbf{p}_1, \dots, \mathbf{p}_K] \in \mathbb{C}^{r \times K}$ is a digital beamforming matrix. Thus, the beamforming optimization problem is given as

$$\begin{aligned} & \underset{\mathbf{B}, \mathbf{P}}{\text{maximize}} && \sum_{k=1}^K \log_2(1 + \text{SINR}_k) \\ & \text{subject to} && |[\mathbf{B}]_{i,j}|^2 = 1, \forall i, j; \\ & && \|\mathbf{BP}\|_F^2 \leq P_{max} \end{aligned} \quad (2.27)$$

2.7. Multi-user System

2.7.1. Signal model

One of the system models addressed in the literature is a downlink MU-MISO system as depicted in **Figure 2.5** that considers a single-cell DL massive MIMO system where a BS is equipped with ULA consisting of N_t antenna elements. The cell is assumed to serve K single-antenna UT. It is assumed that S out of K users are selected to be served simultaneously for a given time and only one data stream is transmitted for each selected user. The transmitted signal, $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$, at the BS is given by

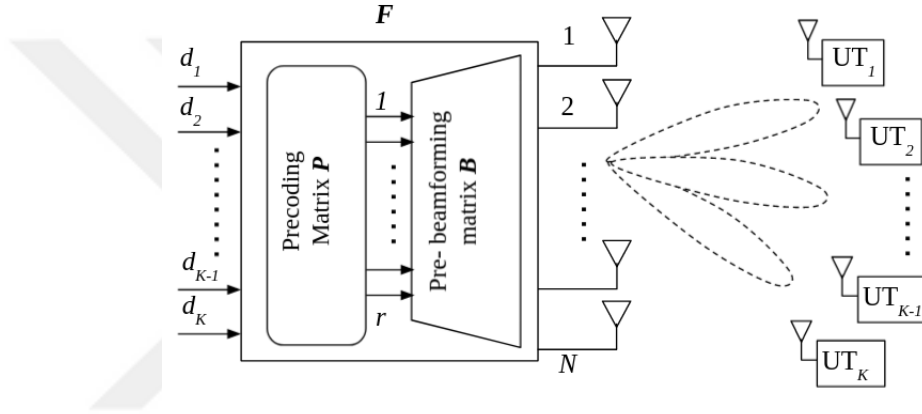


Figure 2.5: DL MU massive MIMO system with precoding matrix $\mathbf{F}$.

$$\mathbf{x} = \sum_{k=1}^K \mathbf{f}_k d_k = \mathbf{F} \mathbf{d} \quad (2.28)$$

where $\mathbf{F} = [\mathbf{f}_1, \dots, \mathbf{f}_K] \in \mathbb{C}^{N_t \times K}$ is a precoding matrix with $\mathbf{f}_k \in \mathbb{C}^{N_t \times 1}$ being a beamforming vector and d_k is the data symbol transmitted to the k^{th} user. The transmitted signal is constrained to have the total transmitted power P_t as $\mathbb{E}[\text{tr}(\mathbf{x}\mathbf{x}^H)] \leq P_t$, where $\mathbb{E}[\cdot]$ and $\text{tr}(\cdot)$ denote expected value operator and trace of a matrix, respectively.

Assuming that the BS transmits only one data streams to each user using r RF chains in total, then $K = r$. The received signals vector, $\mathbf{y} \in \mathbb{C}^{K \times 1}$, at K users is given by

$$\mathbf{y} = \mathbf{H}^H \mathbf{F} \mathbf{d} + \mathbf{n} \quad (2.29)$$

where $\mathbf{H} = [\mathbf{h}_1, \dots, \mathbf{h}_K] \in \mathbb{C}^{N_t \times K}$ is transmission channel matrix of all the users from the BS.

2.7.2. Two-stage precoder

One of example in hybrid beamforming used in multi-user system is two-stage precoder. Adopting the two-stage precoding method proposed in [106], the precoder $\mathbf{F}$ can be considered as a multiplication of a pre-beamforming matrix, $\mathbf{B}$, and a precoder matrix, $\mathbf{P}$, i.e., $\mathbf{F} = \mathbf{B}\mathbf{P}$. In the two-stage precoding technique, it is required to first separate the users into different groups based on their channel covariance matrix. Then, the interference across different groups of users can be suppressed by the pre-beamforming matrix, $\mathbf{B} \in \mathbb{C}^{N_t \times r}$, while the interference within the same group is canceled by $\mathbf{P} \in \mathbb{C}^{r \times K}$. The effective channel after pre-beamforming is denoted as $\hat{\mathbf{H}} = \mathbf{B}^H \mathbf{H} \in \mathbb{C}^{r \times K}$, where r is the effective transmit antenna size. The effective channel is then utilized to generate the second stage matrix $\mathbf{P}$. Here, zero-forcing (ZF) precoder is adopted as $\mathbf{P}$ since it can effectively cancel the interference between users within a given group [107].

The received signal at a user group g can be expressed as

$$\mathbf{y}_g = \underbrace{\mathbf{H}_g^H \mathbf{B}_g \mathbf{P}_g \mathbf{d}_g}_{\text{Desired data of group } g} + \underbrace{\sum_{j=1, j \neq g}^G \mathbf{H}_g^H \mathbf{B}_j \mathbf{P}_j \mathbf{d}_j}_{\text{Interference from other groups}} + \mathbf{n}_g \quad (2.30)$$

where $\mathbf{H}_g = [\mathbf{h}_{g_1}, \dots, \mathbf{h}_{g_{K_g}}] \in \mathbb{C}^{N_t \times K_g}$ is the channel matrix between all K_g number of users in the group g and the BS. We can then define $\mathbf{H} = [\mathbf{H}_1, \dots, \mathbf{H}_G]$ for the total number of users with $K = \sum_{g=1}^G K_g$. Furthermore, $\mathbf{B} = [\mathbf{B}_1, \dots, \mathbf{B}_G]$ is introduced with the pre-beamforming matrix $\mathbf{B}_g \in \mathbb{C}^{N_t \times r_g}$, $\mathbf{P} = \text{blkdiag}([\mathbf{P}_1, \dots, \mathbf{P}_G])$ is a block diagonal matrix composed of the precoding matrix $\mathbf{P}_g \in \mathbb{C}^{r_g \times K_g}$, and $\mathbf{n}_g = [n_{g_1}, \dots, n_{g_{K_g}}]^T$ as the AWGN for users in group g .

As can be seen from (2.30), the inter-group interference can be eliminated if $\mathbf{H}_g^H \mathbf{B}_j \approx 0$. Thus, $\mathbf{B}_g$ can be designed using the Eigen-beamforming method, which is one of the pre-beamforming approaches discussed in [108]. $\mathbf{B}_g$ is then obtained as $\mathbf{B}_g = \mathbf{V}_g$, where $\mathbf{V}_g$ is the unitary eigen matrix of the average channel covariance matrix, $\mathbf{R}_g = \frac{1}{K_g} \sum_{k=1}^{K_g} \mathbf{R}_k$, in group g . The effective channel of the group g after pre-beamforming can be given as $\hat{\mathbf{H}}_g = \mathbf{B}_g^H \mathbf{H}_g = [\hat{\mathbf{h}}_{g_1}, \dots, \hat{\mathbf{h}}_{g_{K_g}}] \in \mathbb{C}^{r_g \times K_g}$. The signal received at the k^{th} user within

the group g can then be expressed as

$$y_{g_k} = \underbrace{\hat{\mathbf{h}}_{g_k}^H \mathbf{p}_{g_k} d_{g_k}}_{\text{Desired symbol}} + \underbrace{\hat{\mathbf{h}}_{g_k}^H \sum_{i=1, i \neq g_k}^{K_g} \mathbf{p}_{g_i} d_i}_{\text{Interference within the group}} + n_{g_k} \quad (2.31)$$

where $\mathbf{P}_g = [\mathbf{p}_{g_1}, \dots, \mathbf{p}_{g_k}]$. The interference within the group is suppressed by ZF precoder, $\mathbf{P}_g = \eta_g \hat{\mathbf{H}}_g (\hat{\mathbf{H}}_g^H \hat{\mathbf{H}}_g)^{-1}$, where $\eta_g^2 = \frac{K_g}{\text{tr}[(\mathbf{B}_g \mathbf{P}_g)^H \mathbf{P}_g \mathbf{B}_g]}$ is the normalization constant to satisfy the power constraint. The signal-to-interference plus noise ratio (SINR) for the user k of the group g is defined as

$$\text{SINR}_{g_k} = \frac{P_{t_k} |\mathbf{h}_{g_k}^H \mathbf{B}_g \mathbf{p}_{g_k}|^2}{P_{t_k} I_g + P_{t_k} I_{g_k} + \sigma_n^2} \quad (2.32)$$

$$I_g = \sum_{j=1, j \neq g}^G \sum_{i=1}^{K_j} |\mathbf{h}_{g_k}^H \mathbf{B}_j \mathbf{p}_{j_i}|^2 \quad (2.33)$$

$$I_{g_k} = \sum_{i=1, i \neq k}^{K_g} |\mathbf{h}_{g_k}^H \mathbf{B}_g \mathbf{p}_{g_i}|^2 \quad (2.34)$$

where I_g and I_{g_k} are interference of the users between groups and within groups, respectively. $P_{t_k} = P_t/K$ is considered to be equal power for all the users. The achievable sum-rate of the k^{th} user in group g is obtained as $C_{g_k} = \log_2(1 + \text{SINR}_{g_k})$, and the total sum-rate of the system is

$$C = \sum_{g=1}^G \sum_{k=1}^{K_g} \log_2(1 + \text{SINR}_{g_k}) \quad (2.35)$$

2.7.3. User grouping and scheduling

2.7.3.1. User grouping

As discussed in **Subsection 2.7.2**, it is required to first separate the users into different groups in order to apply pre-beamforming for each group. The process of user grouping is composed of two stages: user similarity measure and clustering. Improved K-means clustering with WLD similarity measure proposed in [109] and [110] is exploited here, since this combination provides a better sum rate performance than the conventional K-means clustering with the chordal distance [106]. The WLD similarity measure between

the user k and the group g is defined as

$$L(\mathbf{R}_k, \mathbf{V}_g) = \|(\mathbf{U}_k \mathbf{\Lambda}_k^{\frac{1}{2}})^H \mathbf{V}_g\|_F^2 \quad (2.36)$$

Improved K-means clustering method implies that $L(\mathbf{R}_k, \mathbf{V}_g)$ becomes very large when the user k and the group center are very close since $\mathbf{U}_k \approx \mathbf{V}_g$ and $\mathbf{U}_k^H \mathbf{V}_g$ generates a very large value. Therefore, by substituting $\mathbf{U}_k$ of all users in $L(\mathbf{R}_k, \mathbf{V}_g)$ of all the group centers, the users can be assigned to the group with the maximum WLD similarity measure. After each iteration of the group assignment, the centers of the groups are updated by averaging all $\mathbf{R}_{g_k}$, which corresponds to the current group members in their respective group. Mathematically, the updated $\mathbf{V}_g$ of the group g is given by

$$\mathbf{V}_g = \Upsilon \left[\frac{1}{|\mathbb{T}_g|} \sum_{g_k \in \mathbb{T}_g} \mathbf{R}_{g_k} \right] \quad (2.37)$$

where $\Upsilon[\cdot]$ represents the unitary matrix of eigen decomposition. Here, $\mathbb{T}_g$ and $|\mathbb{T}_g|$ are the grouping set and size of the group g , respectively. The next iteration of the group assignment is continued under the condition that the total similarity $L_{tot} = \sum_{g=1}^G \sum_{g_k \in \mathbb{T}_g} L(\mathbf{R}_{g_k}, \mathbf{V}_g)$ of the updated center is larger than that of the previous center by some small constant value ϵ . As for the initialization, the centered user of each group is chosen randomly.

2.7.3.2. User scheduling

After all the users are assigned to the groups with the highest similarity, the pre-beamforming matrix can be generated from the corresponding unitary matrix of the group centers. Since the number of simultaneously served users must be less than the transmit antenna array size at the BS when linear precoding is applied to suppress the inner-group interference, it is required to schedule the users in a group at a given time frame. Among many scheduling techniques, two popular scheduling approaches, SUS algorithm [111] and greedy algorithm [109], [110] are compared in this work.

The SUS user scheduling algorithm selects the users which are approximately orthogonal to each other while having the highest norm of channel gain. On the other hand, the greedy algorithm in [109], [110] first chooses the user with highest received signal power among the users in all groups. Then, as for the next user, a user that can achieve the

highest sum-rate gain is chosen. The sum-rate gain ζ_{g_k} between the previously scheduled user-set $\hat{\mathbb{S}}_g$ and the current scheduled user-set $\mathbb{S}_{g_k}$ contributed by k^{th} user of g^{th} group is obtained by the following method: First $\mathbb{S}_{g_k}$ is created by assigning an unscheduled user k of g^{th} group to its own $\hat{\mathbb{S}}_g$ for $\forall k = [1, \dots, K_g]$. Considering the current user-set and its scheduled user interference set ($\mathbb{S}_{g'_k}$), $\zeta_{g_k} = \max [0, C(\mathbb{S}_{g_k}) - C(\hat{\mathbb{S}}_g)] \forall g = [1, \dots, G]$ are calculated. Then, a maximum gain $\zeta_{gk,max}$ is selected, which corresponds to the second user k_{max} of its own group g_{max} . The process of selecting the next users is also continued in the same manner as the second user iteratively until the gain becomes zero or the maximum number of scheduled users is achieved. The greedy algorithm is summarized in **Algorithm 2.1** [109], [110].

Algorithm 2.1: Greedy User Scheduling Algorithm

```

1: Given: User groups  $\mathbb{T}_g, \hat{\mathbb{S}}_g = \emptyset \forall g = [1, \dots, G], \mathbb{K} = \{1, 2, \dots, K\}, C = 0$ 
2: while  $\sum_g |\hat{\mathbb{S}}_g| \neq \sum_g r_g, \zeta_{gk,max} \neq 0$  or  $\mathbb{K} \neq \emptyset$  do
3:   for  $k \in \mathbb{K}, \forall g$  do
4:     if  $k \in \mathbb{T}_g$  and  $|\hat{\mathbb{S}}_{g_k}| < \mathbb{T}_g$  then
5:        $\mathbb{S}_{g_k} = \{k\} \cup \hat{\mathbb{S}}_g$  and  $\mathbb{S}_{g'_k} = \hat{\mathbb{S}}_{g'}, \forall g' \neq g;$ 
6:
7:       Calculate:  $\zeta_{g_k} = \max [0, C(\mathbb{S}_{g_k}) - C(\hat{\mathbb{S}}_g)]$ 
8:     end if
9:   end for
10:  Find:  $(k_{max}, g_{max}) = \arg \max \zeta_{g_k}$ 
11:  if  $(k_{max}, g_{max}) \neq \emptyset$  then
12:    Update:  $\mathbb{K} = \mathbb{K} \setminus \{k_{max}\}$  and  $\hat{\mathbb{S}}_{g_{k_{max}}} = \hat{\mathbb{S}}_{g_{k_{max}}} \cup \{k_{max}\}$ 
13:  end if
14: end while

```

2.8. Non-Orthogonal Multiple Access

In this section the power domain NOMA system model, signal model, and achievable sum-rate in both DL and UL MISO system are described.

Consider a single-cell MISO-NOMA system where a BS is equipped with uniform array either ULA or UCA consisting of N_t antenna elements as depicted in **Figure 2.6**. The BS serves K single-antenna UTs and the perfect CSI is assumed to be known at the BS. In the case with a single-antenna BS, the beamforming vector can be ignored.

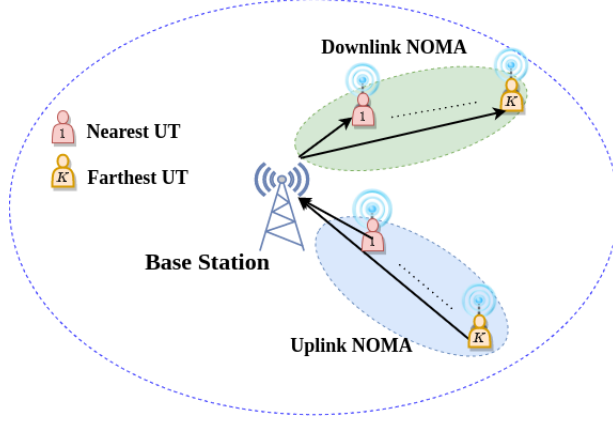


Figure 2.6: MISO-NOMA system model, where BS serves K NOMA-UTs.

In ULA and 2-D UCA, it is assumed that K UTs are selected to be served using NOMA for a given time, and each user transmits only one data stream. We consider that the first UT, $k = 1$, is the nearest user to the BS, followed by UTs $k = 2, \dots, K$. With perfect CSI given at the BS, phased array analog beamforming/combining vectors are adopted based on the nearest UT as $\mathbf{v} = \mathbf{f} = \mathbf{a}_1(\phi_1)$, respectively. In 3-D UCA, 4 clusters of two-UTs are assumed by using hybrid beamforming with 4 RF chains at the BS.

2.8.1. Downlink NOMA transmission

In DL NOMA transmission, by using a directional beamforming vector $\mathbf{v}$ in the same frequency band, a BS transmits a superimposed data stream $x = \sum_{k=1}^K \sqrt{p_k} s_k$ to K UTs, where $s_k; \forall k = 1, 2, \dots, K$, is the data symbol of the UT k . The received signal at k^{th} UT, where the effective channel gain has the following order; $|\mathbf{h}_1^H \mathbf{v}|^2 > |\mathbf{h}_2^H \mathbf{v}|^2 > \dots > |\mathbf{h}_K^H \mathbf{v}|^2$, is expressed as

$$y_k = \mathbf{h}_k^H \mathbf{v} x + n_k, \quad (2.38)$$

$$= \underbrace{\mathbf{h}_k^H \mathbf{v} \sqrt{p_k} s_k}_{\text{Desired signal}} + \underbrace{\sum_{k'=1, k' \neq k}^K \mathbf{h}_k^H \mathbf{v} \sqrt{p_{k'}} s_{k'}}_{\text{Interference from other users}} + n_k, \quad (2.39)$$

where $\mathbf{v} = [v_1, \dots, v_{N_t}]^T \in \mathbb{C}^{N_t \times 1}$ is the normalized transmit beamforming vector, also known as excitation voltages. $p_k = \gamma_k P_t$ is the allocated power of the user k , using the power allocation coefficients, γ_k with $\sum_{k=1}^K \gamma_k = 1$, and P_t is total transmission power.

In order to perfectly decode the desired signal without interference at the nearer UTs, SIC technique, which requires different power allocation as $\gamma_1 < \gamma_2 < \dots < \gamma_K$ such

that lower power values are allocated at the nearer UTs, is applied. Taking advantage of the SIC technique, the UTs located nearer to the BS, which have the stronger channel gain, can successively decode and cancel the signals from the weaker UTs. Therefore, the farthest or cell-edge UT directly decodes the received signal without SIC, hence, there is interference from all of the nearer UTs [5], [112]. Thus, the achievable sum-rate of the nearest UT, without interference, and the rest of the UTs, with other users interference, are defined as

$$R_1^{DL} = \log_2 \left(1 + \frac{|\mathbf{h}_1^H \mathbf{v}|^2 \gamma_1 P_t}{\sigma_1^2} \right), \quad (2.40)$$

$$R_{k=2,\dots,K}^{DL} = \log_2 \left(1 + \frac{|\mathbf{h}_k^H \mathbf{v}|^2 \gamma_k P_t}{|\mathbf{h}_k^H \mathbf{v}|^2 \sum_{k'=1}^{k-1} \gamma_{k'} P_t + \sigma_k^2} \right). \quad (2.41)$$

2.8.2. Uplink NOMA transmission

In UL NOMA system, signals s_k from $k = 1, 2, \dots, K$ UTs are transmitted simultaneously at the same time and frequency to the BS via their respective channel. The superimposed received signal vector at the BS, $\mathbf{y} \in \mathbb{C}^{N_t \times 1}$, is given by

$$\mathbf{y} = \sum_{k=1}^K \mathbf{h}_k \sqrt{p_k} s_k + \mathbf{n}, \quad (2.42)$$

where $\mathbf{n}$ is the AWGN vector at the BS. Unlike DL NOMA, there is no power allocation constraint in UL NOMA since the UTs can utilize maximum power available to them. The received signal of k^{th} UT at the BS after post-coding with the combiner vector $\mathbf{f} \in \mathbb{C}^{N_t \times 1}$ is written by

$$r_k = \underbrace{\mathbf{f}^H \mathbf{h}_k \sqrt{p_k} s_k}_{\text{Desired signal}} + \underbrace{\sum_{k'=1, k' \neq k}^K \mathbf{f}^H \mathbf{h}_{k'} \sqrt{p_{k'}} s_{k'}}_{\text{Interference from other users}} + \mathbf{f}^H \mathbf{n}. \quad (2.43)$$

Here, since the received signal at the nearest UT is decoded without employing SIC due to its highest received power, the interference from the far UTs cannot be removed, while SIC is applied at the far UTs successively to remove the interference from the nearer UTs. Thus, the achievable sum-rates of the farthest cell-edge UT K , without interference, and

the remaining UTs can be expressed by

$$R_K^{UL} = \log_2 \left(1 + \frac{|\mathbf{f}^H \mathbf{h}_K|^2 \gamma_K P_t}{\sigma_K^2} \right), \quad (2.44)$$

$$R_{k=1,\dots,K-1}^{UL} = \log_2 \left(1 + \frac{|\mathbf{f}^H \mathbf{h}_k|^2 \gamma_k P_t}{\sum_{k'=k+1}^K |\mathbf{f}^H \mathbf{h}_{k'}|^2 \gamma_{k'} P_t + \sigma_k^2} \right). \quad (2.45)$$

In the presence of analog beamforming/combining vector $\mathbf{v} = \mathbf{f} = \mathbf{a}(\phi_1)$, the maximum array radiated power for k^{th} UT at the BS in XY-plane can be expressed by (2.46) and (2.47).

$$\zeta^{DL}(\phi_k) = |\mathbf{a}(\phi_k)^H \mathbf{v}|^2 = |\mathbf{a}(\phi_k)^H \mathbf{a}(\phi_1)|^2, \quad (2.46)$$

$$\zeta^{UL}(\phi_k) = |\mathbf{f}^H \mathbf{a}(\phi_k)|^2 = |\mathbf{a}(\phi_1)^H \mathbf{a}(\phi_k)|^2. \quad (2.47)$$

2.9. Partial Non-Orthogonal Multiple Access (P-NOMA)

Over the past few years, many researchers have been paying attention to NOMA due to the fact that NOMA can support more users in a given resource and can provide higher performance compared to OMA technologies such as OFDMA [6]. Since frequency spectrum is a scarce resource in wireless communication systems, NOMA was introduced to increase the system sum-rate without requiring to increase the spectral bandwidth [5]. Compared to OFDMA, power domain NOMA is not based on orthogonal subcarriers, rather it is allowed to transmit a superimposed signal at the same subcarrier, with different power levels. This is then supported with SIC at UT to decode the respective received signal [5]. Due to the shared resource, for example frequency spectrum between the users, there exists interference, which depends on the overlapping ratio of the spectrum. A recent study in [47] proposed a P-NOMA and investigated the effect of spectrum overlapping ratio of the NOMA signals on the achievable rate.

In this section, the basic theory of P-NOMA system, proposed in [47], are briefly described. A downlink system with a single-antenna BS and two single-antenna UTs is considered, where UTs are located at different distances from the BS. Assuming system transmission bandwidth, $B = B_n + B_f$, in conventional NOMA, BS transmits a superimposed signal of both UTs by utilizing total transmission bandwidth for each UT (which is considered as NOMA with fully overlapped B). Signal at the near UT (higher channel

gain with bandwidth B_n) is decoded by using SIC operation while the far UT (lower channel gain with bandwidth B_f) decodes it own signal without SIC operation. Generally, in multi-user scenario with M number of UTs, the received signal, $y_{m,k}$, of m^{th} user at k^{th} subcarrier, given the transmitted symbol $s_{m,k}$, can be written as [5]

$$y_{m,k} = \underbrace{H_{m,k}^H \sqrt{p_m} s_{m,k}}_{\text{Desired symbol}} + \underbrace{H_{m,k}^H \sum_{i=1, i \neq m}^M \sqrt{p_i} s_{i,k}}_{\text{Interference from other users}} + n_k, \quad (2.48)$$

where $H_{m,k}$ and n_k represent the frequency domain channel coefficient and identically distributed (i.i.d.) AWGN with zero-mean and σ_k^2 -variance of the k^{th} subcarrier, respectively. $p_m = \gamma_m P_k$ is the power utilized at the user m , with the power allocation coefficient, γ_m , of the total power at the k^{th} subcarrier, P_k . Given $2N$ total number of subcarriers, P_k is assumed to be uniformly distributed, $P_k = P_t/(2N)$, where P_t is total transmit power.

In order to utilize the given bandwidth efficiently for higher total sum-rate, in P-NOMA system, BS transmits both OMA and NOMA signals by allocating sub-bandwidth (overlapped region R2) to NOMA users and the rest (non-overlapped regions R1 and R3) to OMA users as shown in **Figure 2.7**. Considering each UT occupies half of the total bandwidth, $B_n = B_f = B/2$, BS allocates $0 \leq \alpha \leq 1$ ratio of the far UT bandwidth to the near UT, while far UT utilize $0 \leq \beta \leq 1$ more bandwidth from the near UT, providing the total OR $\rho = \alpha + \beta$. The region R2 is defined as $(N_t - \lfloor \beta N_t \rfloor) \leq k \leq N_t + \lfloor \alpha N_t \rfloor - 1$ while the regions, R1 and R3, are given as $(0 \leq k \leq N_t - \lfloor \beta N_t \rfloor - 1)$ and $(N_t + \lfloor \alpha N_t \rfloor \leq k \leq 2N - 1)$, respectively. The received SINR of the near UT, considering NOR, α , with the channel gain $|H_{n,k}|^2$ is given

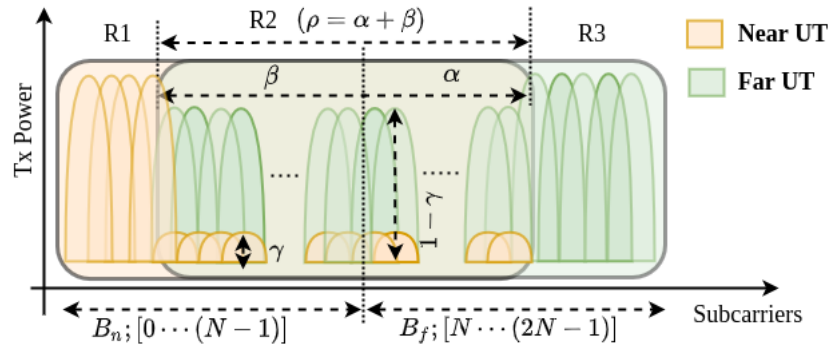


Figure 2.7: P-NOMA system model. B_n is fully occupied by near UT when $\beta = 0$, and B_f is fully utilized by far UT when $\alpha = 0$.

by [47]

$$SINR_n[k] = \begin{cases} |H_{n,k}|^2 P_k / \sigma_k^2, & k \in R1, \\ \frac{|H_{n,k}|^2 \gamma P_k}{\delta |H_{n,k}|^2 (1-\gamma) P_k + \sigma_k^2}, & k \in R2. \end{cases} \quad (2.49)$$

where γ is power allocation coefficient of near UT, and δ (0 or 1) is a SIC effect. Likewise, the received SINR of the far UT, considering Far UT's Overlap Ratio (FOR), β , with the channel gain $|H_{f,k}|^2$ is described by [47]

$$SINR_f[k] = \begin{cases} \frac{|H_{f,k}|^2 (1-\gamma) P_k}{|H_{f,k}|^2 \gamma P_k + \sigma_k^2}, & k \in R2. \\ |H_{f,k}|^2 P_k / \sigma_k^2, & k \in R3. \end{cases} \quad (2.50)$$

Thus, given Δ_{sub} as the frequency subcarrier spacing, the sum-rate of the near and far UTs can be written, respectively, as

$$S_n = \Delta_{sub} \sum_{k \in [R1, R2]} \log_2(1 + SINR_n[k]) \quad (2.51)$$

$$S_f = \Delta_{sub} \sum_{k \in [R2, R3]} \log_2(1 + SINR_f[k]) \quad (2.52)$$

2.10. Related Works

In this section, the related research of the scope of the work in this thesis are discussed.

2.10.1. Direction-of-arrival estimation and mutual coupling

Several high-resolution techniques have been proposed in the literature over the past decades. Among them the most popular techniques are the Capon algorithm [58] and the subspace-based approaches such as Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) [61], [113] and Multiple Signal Classification (MUSIC) [60], [114]. While Capon algorithm suffers from computationally heavy matrix inversion, ESPRIT and MUSIC algorithms suffer from high complexity due to Singular Value Decomposition (SVD) or Eigen Value Decomposition (EVD). As a way of reducing the computational complexity, reduced-rank approaches have been developed [115], [116]. There have been a number of studies which extensively investigate the mutual coupling effect on the performance of conventional MIMO systems with different antenna structures, mostly ULA, UCA, and Uniform Rectangular Array (URA) [31], [32], [79],

[117]–[120]. In the studies of [121], [122], the authors also consider concentric circular antenna array (CCAA), where many concentric circular rings with different radii are placed in XY-plane. They formulated the mutual coupling based on MOM and induced EMF [56], respectively. The study in [119] discussed the effect of mutual coupling and transmit correlation in basic two-user MIMO without considering beamforming. On the other hand, in [31], the author considered uplink multiuser large-scale MIMO system with URA and examined the effect of MC on the sum-rate performance using the optimal beamforming vector. It is worth noticing that most of the studies in the array processing depend on the closed-form mutual coupling formula generated by the induced EMF method.

The algorithms that have been proposed to improve the DoA estimation performance in the presence of unknown MC typically exploit auto-calibration technique [50], [70], [123], [124]. This approach has the ability to estimate DoA and MC jointly without any calibration sources. For 2-Dimensional (2-D) DoA estimation with MC in a UCA, Jiang et al. [125] proposed an algorithm that iteratively modifies the beamspace data. In the work of Wu et al. [71], a subspace-based rank-reduction method is proposed for a uniform rectangular array (URA). However, these methods assume that the signals are uncorrelated. Besides, the iterative calibration process in some of these methods [70], [125] results in a higher computational complexity for massive MIMO systems.

To tackle the issue of coherent signals, various approaches have been considered. However, the spatial smoothing (SS) approach particularly has received more attention [23]–[25]. Moreover, without considering MC in the system, orthogonal projection methods that are based on array steering matrix [126] and signal subspace [127] have also been proposed to estimate the DoA of the coherent signals in low-altitude environments. Especially in the work of Zhou et al. [127], SS method is incorporated to decorrelate the received signals with lower computational complexity. However, as the number of array elements and the sample size increase, the complexity gets higher. With unknown MC, DoA of coherent signals is estimated by using a conventional subspace-based method in conjunction with the SS scheme [128], [129]. In [128], [129], algorithms with the spatial smoothing technique for the estimation of DoAs of the coherent signals without finding the MC estimates are proposed. However, these approaches suffer from the loss of array aperture since they only utilize the middle subarrays. Thus, these methods are not practical for antenna arrays with a large number of elements.

Shi et al. [130] proposed another 2-D DoA estimation algorithm for coherent signals, where the algorithm utilizes the received signal obtained from the whole two parallel ULAs elements in order to reconstruct two new Toeplitz matrices based on fourth-order cumulants (FOC). By using the new Toeplitz matrices [130], the algorithm decorrelates the signals effectively while avoiding the loss of array aperture. In another study, to decorrelate the coherent signals for correct DoA estimation, Shi et al. [131] proposed an improved spatial differencing (ISD), where difference-operation is performed only on auto-correlations of the subarray outputs instead of the whole correlations, along with forward only ISD and backward only ISD. The study can be seen as an extended work of Qi et al. [132]. With the improved ISD, the estimation performance is comparatively better than the conventional spatial smoothing approaches as the effect of additive white or colored noise in the problem is suppressed more effectively. However, this algorithm does not consider the mutual coupling effect of the array and it is also difficult to adapt the algorithm for coupling auto-calibration techniques.

2.10.2. Massive MIMO and beamforming

Beamforming in massive MIMO systems has been attracting enormous research interest in the past years. The main objective in beamforming design is to increase the system capacity in data transmission, in other words, to increase data rate while satisfying the BS power requirements. It has been an open issue in recent years, and many signal processing based algorithms have been proposed to find the optimal solution to the beamforming design. In the literature, many beamforming algorithms, for both analog and digital beamforming, have been proposed to support high data rate transmission by serving many users simultaneously. Especially in MU massive MISO system, hybrid analog and digital beamforming HB design is proposed in order to reduce the hardware cost and the power consuming caused by DAC, also known as RF chains [37], [133]. Two-stage beamforming method [106] is considered as one of popular hybrid beamforming approaches in massive MIMO systems, and OMP and MO are highly utilized hybrid beamforming algorithms in mmWave communication systems [38], [39].

For the case of FDD systems, where uplink and downlink channels are not reciprocal, channel feedback from the users is required at the BS. The size of the feedback overhead is large in large-scale antenna array systems. Hence, a two-stage precoding method is

proposed for FDD systems, in which the outer precoder first reduces the dimension of the original channel based on the inter-group interference. Then, the inner precoder finds the precoding matrix that mitigates the intra-group interference [134], [135]. User grouping and scheduling is required in such two-stage beamforming method. User scheduling in MU beamforming scenario can be performed by learning to improve the system sum-rate or energy efficiency. There are many studies which focus on user scheduling algorithms that increase data rate with good user fairness, less complexity, and high energy efficiency [136]–[139]. Moreover, studies in [140], [141] investigate the effect of channel prediction on beamforming design. Especially in [141], the authors propose a joint beamforming and scheduling design using the predicted next block CSI and show the effectiveness of the channel prediction in user scheduling. However, the carrier frequencies used in these studies are less than 6 GHz. Thus, **Section 3.3** will focus on analysing the effect mmWave fast fading Doppler channel on the user grouping and scheduling of MIMO system with two-stage beamforming.

The above-mentioned conventional approaches are complicated due to the non-convex optimization problem of beamforming vectors with their constant modulus constraint [38]. Thus, recently, these algorithms are being replaced by DL-based beamforming since Deep Neural Networks (DNN)s can solve highly complicated non-convex problems with low computational complexity, thereby reducing the delay in tackling the design problem on the fly [142]–[144]. In [145], a deep learning method was first introduced for designing hybrid beamformer. Unsupervised learning method is exploited to train the DNN as an auto-encoder using Stochastic Gradient Descent (SGD) algorithm with momentum [146], [147]. It is proved that performance (bit-error-rate (BER), SE, Mean-Square-Error (MSE)) of the DNN-based precoder is better than that of the conventional beamforming schemes [38], [148] while providing lower computational complexity.

It is also worth mentioning that Xia et al. in [142] address the problem of optimal beamforming design in MU MISO systems using deep learning. Three different deep learning-based frameworks using CNN are proposed, which solve the following optimization problems: 1) SINR balancing problem, 2) power minimization problem, and 3) sum-rate maximization problem. Supervised learning is used to train the networks of the first two problems, while hybrid supervised and unsupervised learning is used in the last problem for better performance. In [149], a deep network is trained to choose between ZF and MRT

DB that maximizes the total capacity of two users interference MISO system (i.e., two transmitters with the respective single-antenna users). The desired and interfered channel vectors of both transmitters are used as input to the Fully-Connected Neural Network (FCNN) with several hidden layers.

Another deep learning-based HB is proposed in [144] for single-user MISO systems. FCNN is trained to achieve an optimal analog beamforming vector that maximizes the system capacity while satisfying constant modulus of analog PSs. Digital beamformer is initially obtained by satisfying the transmit power constraint. Then, given the digital beamformer, the analog beamformer is optimized via the offline FCNN and pre-defined Lambda layer that transforms the output (beamforming angles) of FCNN to a complex-valued vector. The proposed beamformer is resilient to imperfect channel since FCNN is trained using the estimated channel as an input vector and perfect channel information in calculating the loss function. The authors use unsupervised learning, which employs the negative system capacity as the loss function, without the need of labeled outputs. Simulation results show that the proposed FCNN network outperforms the conventional HB methods [39], [150] in imperfect CSI scenario. However, their proposed BFNN consists of multiple Fully-Connected (FC) layers, which are very computationally expensive because of the high number of network parameters. Thus, the solution to low complexity deep-learning based beamforming is presented in **Section 3.2**.

2.10.3. Non-orthogonal multiple access (NOMA) with emerging technologies

A number of research on NOMA has been conducted, regarding its performance, power and subcarrier allocation, user pairing and scheduling, integration with MIMO beamforming, and more [5], [19], [20], [151]–[157]. In order to improve the sum-rate performance, the study in [158] proposes a multi-beam NOMA architecture with HB, where each NOMA user cluster is supported by multiple analog beams formed from one RF chain. A beam splitting is realized by adaptively dividing the whole transmit antenna array elements, related to the interested RF chain, into several subarrays (the same number of subarrays as the number of users in the cluster). Different PSs-based analog beamformer for each subarray is designed that directs the sub-beams to the respective users in the cluster.

The task of user grouping and antenna allocation among the users in the group for beam

splitting is the most important part in designing the HB with multiple beams. Hence, the authors in [158] propose a joint user grouping and antenna allocation algorithm first, which maximizes the achievable sum-rate, based on the Line-of-Sight (LOS) DoDs and the channel path gains of all the users. Then, ZFB based on the equivalent channel is employed as DB, and given the effective channel and DB, power allocation is performed by maximizing the total sum-rate. The proposed scheme is more flexible in pairing users with an arbitrary DoDs distribution, and it can also serve several user groups effectively, leading to higher MU diversity.

In addition to the traditional NOMA system, there are also many studies that proposed hybrid NOMA-OMA systems, which dynamically allocate either NOMA or OMA user at each subcarrier, based on the criteria such as user fairness, total sum-rate, complexity, and so on [46], [159]. In the recent study of [47], the authors investigated a partial overlapping scenario, where a two-user system partially utilizes the total bandwidth for both OMA and NOMA systems, since interference in NOMA system occurs due to fully overlapped signal of the users. The authors proposed a P-NOMA system, which improves the total sum-rate by controlling the ORs between the signals of the UT. In [160], the authors also investigated the performance of the P-NOMA system by considering the user fairness and proposed a heuristic algorithm to search the ORs. However, in these studies, prior to searching for the ORs, the authors assumed that power allocation has already been obtained via different approaches, such as fractional transmission power allocation (FTPA) [161] and the power allocation method in [45]. Thus, in this thesis, **Section 3.5** will propose a low complexity power allocation algorithm of P-NOMA system with user fairness, then **Section 3.6** will discuss an improved P-NOMA called PB-NOMA by considering overlapped users.

In recent years, numerous studies have been published that focus on RIS in wireless communication systems since RIS is one of the potential technologies for beyond 5G wireless networks [162]–[164]. Low-cost passive reflecting elements of RIS enable wireless channel reconfiguration by a programmable controller and provide an additional path to the UTs that are at Non-Line-of-Sight (Non-LOS) region so as to increase the received power level or introduce a diverse path. In single cell networks, RIS technique has been integrated with NOMA system to further increase the OP, SE, and EE [165]–[168].

In the case of multi-cell networks, adjacent cells generate co-channel Inter-Cell Interference (ICI), which leads to the low received SNRs at the cell-edge users. In order to mitigate the effect of ICI, 4G systems proposed CoMP transmission with OMA [169]. To benefit from the NOMA approach, research on multi-cell NOMA with CoMP technique has been conducted by several groups. For example, in [170], different solutions of ICI mitigation in a two-user downlink NOMA system were proposed. One of the solutions was a JT-CoMP, where the cell-edge can simultaneously receive the same signal from the BSs of the adjacent cells without treating them as interference. Power allocation problem of the downlink CoMP-NOMA system, on the other hand, was investigated in [171] and [7]. In [172], the author explored the ergodic rate performance analysis of RIS assisted CoMP-NOMA. The authors considered two cells composed of one cell-center user in each cell with one CoMP cell-edge user that receives joint transmission from both BSs. The analytical expression of ergodic rate is derived and compared with simulation results. It can be observed from the aforementioned literature that the OP performance of the CoMP - NOMA networks in the presence of RIS has not been analysed yet, that will be the focus of **Section 3.7** in this thesis work.

CHAPTER 3

3. EXPERIMENTAL PART

In this chapter, the methodologies, the proposed systems and the proposed algorithms that solve the issue of computational complexity and the spectral efficiency are described in details, along with simulation setup under each topic.

3.1. Reduced-Rank Joint Estimation Of DoA With Mutual Coupling

In this section, a reduced-rank joint estimation of DoA with unknown MC in the presence of coherent signals is presented. This algorithm is an extended version of the combined technique of reduced-rank joint iterative optimization (JIO) algorithm [115] and auto-calibration of MC [70], introduced in [173]. In this proposed algorithm, a reduced-rank matrix is used to transform the received signal vector and the steering vector to a lower rank, and a secondary reduced-rank weighting vector is employed to compute the Capon power spectrum. To decorrelate the coherent signal, the JIO algorithm is modified and integrated with the Forward Backward Spatial Smoothing (FBSS) process in the presence of MC. Then, MC and DoAs are jointly estimated with the iterative auto-calibration approach [70] based on the Minimum Variance (MV) criterion. After estimating the MC coefficients from auto-calibration algorithm, an additional FBSS-JIO is performed with the newly estimated MC coefficients in order to obtain more accurate DoA estimates. The main methodologies of this work are:

1. Formulating the JIO-FBSS algorithm suitable for mutual coupling auto-calibration,
2. Exploiting a new reduced-rank spatially smoothed covariance matrix in the MV based joint estimation of DoAs and MC while maintaining low complexity.

In order to transform the covariance matrix into a non-singular matrix, a preprocessing method named FBSS technique is applied to the array outputs. For FBSS, the array outputs are first grouped into uniformly overlapping subarrays with the size z . Then, a spatially smoothed covariance matrix is obtained by averaging the covariance matrices of the subarray outputs [23], [24]. Without mutual coupling effect, the p^{th} forward subarray, $\mathbf{x}_{f,p}(k)$, and p^{th} backward subarray, $\mathbf{x}_{b,p}(k)$, can be constructed as

$$\mathbf{x}_{f,p}(k) = \mathbf{A}_{fb} \mathbf{B}^{p-1} \mathbf{s}(k) + \mathbf{n}_{f,p}(k) \in \mathbb{C}^{z \times 1} \quad (3.1)$$

$$\mathbf{x}_{b,p}(k) = \mathbf{A}_{fb} \mathbf{B}^{p-1} \mathbf{B}^{(z-1)*} \mathbf{s}^*(k) + \mathbf{n}_{b,p}(k) \in \mathbb{C}^{z \times 1} \quad (3.2)$$

where

$$\mathbf{A}_{fb} = [\mathbf{a}_{fb}(\theta_1), \dots, \mathbf{a}_{fb}(\theta_M)] \in \mathbb{C}^{z \times M} \quad (3.3)$$

$$\mathbf{a}_{fb}(\theta_m) = \left[1, e^{-j \frac{2\pi d}{\lambda} \sin(\theta_m)}, \dots, e^{-j \frac{2\pi(z-1)d}{\lambda} \sin(\theta_m)} \right]^T \in \mathbb{C}^{z \times 1} \quad (3.4)$$

$$\mathbf{B} = \text{diag} \left\{ e^{-j \frac{2\pi d}{\lambda} \sin(\theta_1)}, \dots, e^{-j \frac{2\pi d}{\lambda} \sin(\theta_M)} \right\} \in \mathbb{C}^{M \times M} \quad (3.5)$$

where $()^*$ denotes a complex conjugate. $\mathbf{n}_{f,p}(k) \in \mathbb{C}^{z \times 1}$ and $\mathbf{n}_{b,p}(k) \in \mathbb{C}^{z \times 1}$ are the AWGNs of the subarrays. The $(p-1)^{th}$ power of the diagonal matrix $\mathbf{B}$ acts as a forward-moving window, which helps to select the forward subarrays starting from the first antenna element. On the other hand, $\mathbf{B}^{p-1} \mathbf{B}^{(z-1)*}$ groups the backward subarrays starting from the last antenna element. The next section discusses a detailed approach that performs DoA estimation under unknown MC for coherent signals with low computational complexity and yet offering a similar performance as the conventional approaches with known MC.

3.1.1. The proposed algorithm

The proposed algorithm initially obtains the reduced-rank FBSS covariance matrix, which is then employed in the MV based cost function of the auto-calibration method to estimate the MC and DoAs iteratively. FBSS process is firstly performed on the array outputs to decorrelate the received signal. Then, the covariance matrix of the smoothed array output is reduced to a lower dimension by using JIO based reduced rank method. Finally the reduced covariance matrix is applied to the MC auto-calibration process to jointly estimate DoAs and MC coefficients. The complete procedure of the proposed algorithm is summarized in **Algorithm 3.2** in **Subsection 3.1.1.2**.

3.1.1.1. Spatial smoothing in the presence of mutual coupling

Here, the FBSS method [24] is exploited, which initially divides the original array output into $P = N_t - z + 1$ numbers of overlapping subarrays in both forward and backward directions at k^{th} snapshot in time domain. Mathematically, in the presence of MC, p^{th} forward subarray, $\mathbf{x}_{f,p}(k)$, and p^{th} backward subarray, $\mathbf{x}_{b,p}(k)$, can be written as

$$\mathbf{x}_{f,p}(k) = \mathbf{C}_{fb} \mathbf{A}_{fb} \mathbf{B}^{p-1} \mathbf{s}(k) + \mathbf{n}_{f,p}(k) \in \mathbb{C}^{z \times 1} \quad (3.6)$$

$$\mathbf{x}_{b,p}(k) = \mathbf{C}_{fb} \mathbf{A}_{fb} \mathbf{B}^{p-1} \mathbf{B}^{(z-1)*} \mathbf{s}^*(k) + \mathbf{n}_{b,p}(k) \in \mathbb{C}^{z \times 1} \quad (3.7)$$

where

$$\mathbf{C}_{fb} = \text{Toeplitz} \left\{ [\mathbf{c}^T, \mathbf{0}_{1 \times (z-L)}] \right\} \in \mathbb{C}^{z \times z} \quad (3.8)$$

To determine the reduced-rank subarray output and its covariance matrix recursively, each subarray output is first determined in the JIO based rank reduction process. Then, by using all P subarray outputs, the FBSS covariance matrix at k^{th} snapshot is calculated as

$$\mathbf{R}_{fb}(k) = \frac{1}{2P} \sum_{p=1}^P (\mathbf{R}_{f,p}(k) + \mathbf{R}_{b,p}(k)) \in \mathbb{C}^{z \times z} \quad (3.9)$$

3.1.1.2. JIO-FBSS based reduced-rank DOA estimation with mutual coupling calibration

As a first step, the JIO based reduced rank method is modified to include the effect of MC. Using a rank reduction matrix $\mathbf{T}_{r,fb} \in \mathbb{C}^{z \times r}$ with reduced size r , the reduced-rank p^{th} forward and backward subarray outputs are obtained as

$$\bar{\mathbf{x}}_{f,p}(k) = \mathbf{T}_{r,fb}^H \mathbf{x}_{f,p}(k) \in \mathbb{C}^{r \times 1} \quad (3.10)$$

$$\bar{\mathbf{x}}_{b,p}(k) = \mathbf{T}_{r,fb}^H \mathbf{x}_{b,p}(k) \in \mathbb{C}^{r \times 1} \quad (3.11)$$

Then, the new reduced-rank FBSS covariance matrix is obtained from (3.9) by using reduced-rank covariance matrices, $\bar{\mathbf{R}}_{f,p}(k)$ and $\bar{\mathbf{R}}_{b,p}(k)$. Due to the symmetric structure of the ULA array, the matrix $\mathbf{C}_{fb}$ affecting the original steering vector can be transformed into a coupling vector $\mathbf{c}$ as

$$\mathbf{C}_{fb} \mathbf{a}_{fb}(\theta) = \mathbf{T} [\mathbf{a}_{fb}(\theta)] \mathbf{c} \in \mathbb{C}^{z \times 1} \quad (3.12)$$

where $\mathbf{T}[\mathbf{a}_{fb}(\theta)] \in \mathbb{C}^{z \times L}$ is a ULA transformation matrix [50]. Consequently, $\bar{\mathbf{a}}_{fb}(\theta)$, the reduced-rank steering vector perturbed by MC becomes

$$\bar{\mathbf{a}}_{fb}(\theta) = \mathbf{T}_{r,fb}^H \mathbf{T}[\mathbf{a}_{fb}(\theta)] \mathbf{c} = \bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta)] \mathbf{c} \in \mathbb{C}^{r \times 1} \quad (3.13)$$

where $\bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta)] = \mathbf{T}_{r,fb}^H \mathbf{T}[\mathbf{a}_{fb}(\theta)]$ is the reduced-rank $\mathbf{T}[\mathbf{a}_{fb}(\theta)]$. Given the new reduced rank variables, DoAs can be estimated by solving a modified MV based reduced-rank optimization problem in the presence of MC [72] as

$$\begin{aligned} \hat{\theta}_m = \arg \min_{\theta} \quad & \bar{\mathbf{w}}_{\theta}^H \mathbf{T}_{r,fb}^H \mathbf{R}_{fb} \mathbf{T}_{r,fb} \bar{\mathbf{w}}_{\theta} \\ \text{subject to} \quad & \bar{\mathbf{w}}_{\theta}^H \mathbf{T}_{r,fb}^H \mathbf{T}[\mathbf{a}_{fb}(\theta)] \mathbf{c} = 1 \end{aligned} \quad (3.14)$$

Since the objective function, $\bar{\mathbf{w}}_{\theta}^H \mathbf{T}_{r,fb}^H \mathbf{R}_{fb} \mathbf{T}_{r,fb} \bar{\mathbf{w}}_{\theta}$, in (3.14) is in quadratic form with linear constraint and the fact that $\mathbf{R}_{fb}$ is a symmetric positive semi-definite matrix, the function is convex [174]. Hence, the unknown variables $\bar{\mathbf{w}}_{\theta}(k)$ and $\mathbf{T}_{r,fb}(k)$ at each k^{th} snapshot are derived via the constrained least squares (LS) approach with Lagrange multiplier method as in the work of Wang et al. [115], resulting in (3.18) and (3.19) of **Algorithm 3.1** given below.

By recursively updating $\mathbf{T}_r(k)$ and $\bar{\mathbf{w}}_{\theta}(k)$ and substituting them into (3.14), the reduced-rank Capon's power spectrum $P_r(\theta)$ is obtained as

$$P_r(\theta) = \left(\mathbf{c}^H \bar{\mathbf{T}}^H[\mathbf{a}_{fb}(\theta)] \hat{\mathbf{R}}_{fb}^{-1}(K) \bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta)] \mathbf{c} \right)^{-1} \quad (3.20)$$

Using a forgetting factor γ , the estimate of $\bar{\mathbf{R}}_{fb}$ is recursively updated in each snapshot, and the estimated covariance matrix $\hat{\mathbf{R}}_{fb}(K)$ is obtained after K snapshots [175]. DoAs are then estimated by finding the peaks of the reduced-rank power spectrum $P_r(\theta)$. The overall algorithm is summarized in **Algorithm 3.1**.

In order to calibrate the coupling for the precise DoA estimation, the JIO-FBSS is combined with the auto-calibration method. Compared to the auto-calibration method [70], which is based on MUSIC algorithm, the cost function to be minimized in the proposed method is based on MV criterion. This is because the algorithm of Wang et al. [70] is valid only when the number of sources is less than the number of array sensors, or when $M \leq \left\lfloor \frac{(N_t-1)}{2} \right\rfloor$. However, in this study, N_t is reduced to r , where $r \ll N_t$, and therefore the condition for the use of the existing subspace-based calibration method is not fulfilled.

In JIO-FBSS, DoAs are estimated by maximizing the output power spectrum given

Algorithm 3.1: JIO-FBSS Algorithm with MC

```

1: for  $\theta_i = -90 : \Delta : 90$  do ; ▷  $\Delta$  is a searching step size
2:   Initialize:  $\mathbf{T}_{r,fb}(0) = \begin{bmatrix} \mathbf{I}_{r \times r}^T & \mathbf{0}_{r \times (z-r)}^T \end{bmatrix}^T$ ;
3:    $\hat{\mathbf{R}}_{fb}(0) = \delta \mathbf{I}_{z \times z}$ ;  $\hat{\mathbf{R}}_{fb}(0) = \delta \mathbf{I}_{r \times r}$ ;  $\delta > 0$  ;
4:   for  $k = 1 : 1 : K$  do ▷ Recursive with snapshot  $k = 1, 2, \dots, K$ 
5:     for  $p = 1 : 1 : P$  do ▷ FBSS with subarray  $p = 1, 2, \dots, P$ 
6:       Calculate  $\mathbf{x}_{f,p}(k)$  and  $\mathbf{x}_{b,p}(k)$  using Subsection 3.1.1.1 and Subsection 3.1.1.1;
7:       Calculate  $\bar{\mathbf{x}}_{f,p}(k)$  and  $\bar{\mathbf{x}}_{b,p}(k)$  using Subsection 3.1.1.2 and Subsection 3.1.1.2;
8:       Calculate  $\mathbf{R}_{f,p}(k) = \mathbf{x}_{f,p}(k)\mathbf{x}_{f,p}^H(k)$  and  $\mathbf{R}_{b,p}(k) = \mathbf{x}_{b,p}(k)\mathbf{x}_{b,p}^H(k)$ ;
9:     end for
10:    Update  $\hat{\mathbf{R}}_{fb}(k)$  and  $\mathbf{T}_{r,fb}(k)$  as follows:
        
$$\bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta_i)] = \mathbf{T}_{r,fb}^H(k-1)\mathbf{T}[\mathbf{a}_{fb}(\theta_i)]; \quad (3.15)$$


$$\hat{\mathbf{R}}_{fb}(k) = \gamma \hat{\mathbf{R}}_{fb}(k-1) + \frac{1}{2P} \sum_{p=1}^P (\mathbf{R}_{f,p}(k) + \mathbf{R}_{b,p}(k)); \quad (3.16)$$


$$\hat{\mathbf{R}}_{fb}(k) = \gamma \hat{\mathbf{R}}_{fb}(k-1) + \frac{1}{2P} \sum_{p=1}^P (\bar{\mathbf{R}}_{f,p}(k) + \bar{\mathbf{R}}_{b,p}(k)); \quad (3.17)$$


$$\bar{\mathbf{w}}_{\theta}(k) = \frac{\hat{\mathbf{R}}_{fb}^{-1}(k)\bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta_i)]\mathbf{c}}{\mathbf{c}^H \bar{\mathbf{T}}^H[\mathbf{a}_{fb}(\theta_i)] \hat{\mathbf{R}}_{fb}^{-1}(k) \bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta_i)] \mathbf{c}}; \quad (3.18)$$


$$\mathbf{T}_{r,fb}(k) = \frac{\hat{\mathbf{R}}_{fb}^{-1}(k)\mathbf{T}[\mathbf{a}_{fb}(\theta_i)]\mathbf{c}}{\mathbf{c}^H \mathbf{T}^H[\mathbf{a}_{fb}(\theta_i)] \hat{\mathbf{R}}_{fb}^{-1}(k) \mathbf{T}[\mathbf{a}_{fb}(\theta_i)] \mathbf{c}} \frac{\bar{\mathbf{w}}_{\theta}^H(k)}{\|\bar{\mathbf{w}}_{\theta}(k)\|^2}; \quad (3.19)$$

11:   end for
12:   Calculate:  $P_r(\theta_i)$  using (3.20);
13: end for
return  $P_r(\boldsymbol{\theta}) = [P_r(\theta_1), P_r(\theta_2), \dots, P_r(\theta_S)]$  ▷  $S$  is length of  $\boldsymbol{\theta}$ 

```

in (3.20). In this algorithm, DoAs and MC are iteratively updated by minimizing the sum of the inverse power spectrum, which corresponds to the true DoAs. Thus, the quadratic minimization problem based on Capon's power spectrum can be expressed as

$$\mathbf{c} = \arg \min_{\mathbf{c}} \sum_{m=1}^M \left[\left(\mathbf{c}^H \bar{\mathbf{T}}^H[\mathbf{a}_{fb}(\theta_m)] \hat{\mathbf{R}}_{fb}^{-1}(K) \bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta_m)] \mathbf{c} \right)^{-1} \right]^{-1} = \mathbf{c}^H \mathbf{G}(\boldsymbol{\theta}) \mathbf{c}$$

subject to $\|\mathbf{c}\| = 1$

(3.21)

where $\mathbf{G}(\boldsymbol{\theta}) = \sum_{m=1}^M \bar{\mathbf{T}}^H[\mathbf{a}_{fb}(\theta_m)] \hat{\mathbf{R}}_{fb}^{-1} \bar{\mathbf{T}}[\mathbf{a}_{fb}(\theta_m)]$. The solution to (3.21) has already been discussed in the work of Wang et al. [70] and is given as $\mathbf{c} = \mathbf{e}_{\min}\{\mathbf{G}(\boldsymbol{\theta})\}$, where $\mathbf{e}_{\min}\{\cdot\}$ denotes the eigenvector that corresponds to the smallest eigenvalue. After iteratively estimating $\mathbf{c}$ and $\{\hat{\theta}_m^{(i)}\}_{m=1}^M$ by the approach in **Algorithm 3.2**, the estimated $\mathbf{c}$ is determined when the convergence is reached. The final DoAs are estimated by using the

impinging on the array from $\theta = [-55^\circ, 40^\circ, 45^\circ, 60^\circ]$, randomly chosen complex attenuation vector, $\mathbf{b}$, is set to $\mathbf{b} = [1, -0.3 - j0.7, 0.2 + j0.3, -0.1 + j0.6]$. A MC vector of $\mathbf{c} = [1, 0.6325 + j0.3946, 0.3514 + j0.2192]$ as given in the work of Sellone et al. [123], $\Delta = 0.5^\circ$ for a thorough scan and $\gamma = 0.998$ as given in the study of Wang et al. [115]. Following the work of Shan et al. [23], the subarray size for FBSS is chosen as $z = 41$, which results in $P = 10$ subarrays. The reduced rank is set to $r = 5$ since the rank that affects the resolution is between $r_{min} = 3$ and $r_{max} = 7$, which has been empirically proved in [115]. The simulations results are obtained based on 10^3 simulation runs ($N_s = 10^3$). The workstation that is used to perform the simulations has the following specifications: the processor is Intel(R) Xeon(R) CPU E5-2650 v3 2.30GHz x 10 and the memory is 188.8GiB.

3.2. Impact Of Mutual Coupling On Power-Domain Non-Orthogonal Multiple Access (NOMA)

In this section, the performance of DL and UL NOMA systems in the presence of mutual coupling is investigated based on different antenna array configurations. Non-invasive technique for compensation of mutual coupling is utilized for both DL [176] and UL [177] transmissions. The followings summarize the methodologies used in this work:

1. The modified achievable sum-rate of NOMA system in the presence of mutual coupling is derived based on the effect of mutual coupling on channel gain of the K numbers of UTs.
2. Mutual coupling is compensated for both DL and UL transmissions, and numerical results on the achievable sum-rate of NOMA system are analyzed and compared to that of the coupled system, employing three different antenna array structure mentioned above.

3.2.1. Achievable sum-rate in the presence of MC

A directional mmWave channel based on geometric model is adopted in this work, where only LOS channel is considered due to its channel gain dominant over Non-LOS channel gain [178], [179]. In the presence of mutual coupling, based on the coupled channel vector,

the received signal at the k^{th} UT in the DL transmission becomes

$$y_{kMC} = \underbrace{\mathbf{h}_k^H \mathbf{C}^H \mathbf{v} \sqrt{p_k} s_k}_{\text{Desired signal}} + \underbrace{\sum_{k'=1, k' \neq k}^K \mathbf{h}_k^H \mathbf{C}^H \mathbf{v} \sqrt{p_{k'}} s_{k'}}_{\text{Interference from other users}} + w_k. \quad (3.22)$$

The effective achievable sum-rate of DL NOMA without compensation is expressed as

$$\hat{R}_k^{DL} = \log_2 \left(1 + \frac{|\mathbf{h}_k^H \mathbf{C}^H \mathbf{v}|^2 p_k}{\sum_{k'=1, k' \neq k}^K e_{k'} |\mathbf{h}_k^H \mathbf{C}^H \mathbf{v}|^2 p_{k'} + \sigma_k^2} \right), \quad (3.23)$$

where $e_{k'} \in \{0, 1\}$ is the SIC decision value based on the effective channel gain. $e_{k'} = 0$ means that there exists no interference from UT k' , in other words, the signal of UT k' is decoded first and then cancelled at the UT k . On the other hand, $e_{k'} = 1$ represents the interference from UT k' , hence, the signal of the UT k' is considered as noise at the UT k without decoding and cancellation process.

In multi-group NOMA system, using the hybrid beamformer of g^{th} group, $\hat{\mathbf{v}}_g = \mathbf{V}_{rf} \mathbf{b}_g$, and considering $K = 2$ UTs in each group, the effective achievable sum-rates of the near and far UTs with MC are respectively formulated as

$$\hat{R}_{g_1}^{DL} = \log_2 \left(1 + \frac{|\mathbf{h}_{g_1}^H \mathbf{C}^H \hat{\mathbf{v}}_g|^2 p_1}{e_2 |\mathbf{h}_{g_1}^H \mathbf{C}^H \hat{\mathbf{v}}_g|^2 p_2 + I_1 + \sigma_1^2} \right), \quad (3.24)$$

$$\hat{R}_{g_2}^{DL} = \log_2 \left(1 + \frac{|\mathbf{h}_{g_2}^H \mathbf{C}^H \hat{\mathbf{v}}_g|^2 p_2}{e_1 |\mathbf{h}_{g_2}^H \mathbf{C}^H \hat{\mathbf{v}}_g|^2 p_1 + I_2 + \sigma_2^2} \right), \quad (3.25)$$

where $I_k = \sum_{g' \neq g}^G |\mathbf{h}_{g_k}^H \mathbf{C}^H \hat{\mathbf{v}}_{g'}|^2 P_{g'}$ is the inter-group interference, affecting the k^{th} UT with total power of the group g' , $P_{g'}$.

In UL transmission, the received signal of the k^{th} UT at the BS by considering the MC effect is given as

$$r_{kMC} = \underbrace{\mathbf{f}^H \mathbf{C} \mathbf{h}_k \sqrt{p_k} s_k}_{\text{Desired signal}} + \underbrace{\sum_{k'=1, k' \neq k}^K \mathbf{f}^H \mathbf{C} \mathbf{h}_{k'} \sqrt{p_{k'}} s_{k'}}_{\text{Interference from other users}} + \mathbf{f}^H \mathbf{n}. \quad (3.26)$$

The effective achievable sum-rate of UL NOMA without compensation can be written as

$$\hat{R}_k^{UL} = \log_2 \left(1 + \frac{|\mathbf{f}^H \mathbf{C} \mathbf{h}_k|^2 p_k}{\sum_{k'=1, k' \neq k}^K e_{k'} |\mathbf{f}^H \mathbf{C} \mathbf{h}_{k'}|^2 p_{k'} + \sigma_k^2} \right). \quad (3.27)$$

Assuming no mutual coupling compensation is applied in the system, hence, the analog beamforming vector is $\mathbf{v} = \mathbf{a}(\phi_1)$, the channel gain of the k^{th} UT in DL transmission can

be calculated according to (2.23) as

$$h_k = \frac{N_t}{\rho_k} |\alpha_k^H|^2 |\mathbf{a}(\phi_k)^H \mathbf{C}^H \mathbf{a}(\phi_1)|^2. \quad (3.28)$$

In similar fashion, the received channel gain of the UTs in UL transmission can be obtained using the received beam power in (2.24).

In this study, analog beamforming/combining based on the steering vector of the nearest UT is employed since it is aimed to avoid beamforming interference at the nearest UT for the sake of the perfect SIC operation. Based on the coupled channel gains of the UTs, the following scenarios can be assumed and the SIC decision variable $e_{k'}$ in (3.23)-(3.25) and (3.27) can be chosen accordingly.

1. *Case 1 DL*: Considering the coupled effective gain of the UTs in the following order; $\zeta_{MC}^{DL}(\phi_1) > \zeta_{MC}^{DL}(\phi_2) > \dots > \zeta_{MC}^{DL}(\phi_K)$ with $\gamma_1 < \gamma_2 < \dots < \gamma_K$, SIC can be performed correctly at the near users by substituting $e_{k'}$ in (3.23)-(3.25) as follows

$$e_{k'} = \begin{cases} 0, & \text{if } k' > k, \\ 1, & \text{if } k' < k. \end{cases}$$

2. *Case 2 DL*: In the case of significantly distorted beam pattern in **Figure 4.6a**, assuming the farthest UT K is located at the peak direction of the distorted beam, the coupled effective gain of the UTs have become $\zeta_{MC}^{DL}(\phi_1) \ll \zeta_{MC}^{DL}(\phi_2) \ll \dots \ll \zeta_{MC}^{DL}(\phi_K)$, that makes the effective channel gains, $h_1 < h_2 < \dots < h_K$. Thus, the far users should be considered as strong users, consequently $\gamma_1 > \gamma_2 > \dots > \gamma_K$, and SIC should be performed at the far users successively in (3.23)-(3.25), given that

$$e_{k'} = \begin{cases} 0, & \text{if } k' < k, \\ 1, & \text{if } k' > k. \end{cases}$$

However, due to unawareness of MC at the BS, the SIC operation cannot be performed at the correct UTs, resulting reduce in sum-rate.

3. *Case 3 UL*: Similar to *Case 1* and 2, based on the effective coupled channel gain, when $\zeta_{MC}^{UL}(\phi_1) > \zeta_{MC}^{UL}(\phi_2) > \dots > \zeta_{MC}^{UL}(\phi_K)$, SIC is correctly applied at the far UTs such that $e_{k'} = 0; \forall k' < k$, and $e_{k'} = 1; \forall k' > k$. In the presence

of mutual coupling, resulting $\zeta_{MC}^{UL}(\phi_1) \ll \zeta_{MC}^{UL}(\phi_2) \ll \dots \ll \zeta_{MC}^{UL}(\phi_K)$ with $h_1 < h_2 < \dots < h_K$, SIC should be successively performed at the near UTs with $e_{k'} = 0$; $\forall k' > k$, and $e_{k'} = 1$; $\forall k' < k$ in (3.27).

In 3-D UCA, where G number of groups are served by the BS, beams pointing to different directions are generated by hybrid beamforming, where two UTs are supported by NOMA in each group. The channel matrix is given as $\mathbf{H} = [\mathbf{h}_{11}, \mathbf{h}_{12}, \dots, \mathbf{h}_{G1}, \mathbf{h}_{G2}] \in \mathbb{C}^{N_t \times 2G}$. The hybrid beamforming matrix consists of steering vector-based analog beamforming with respect to the near UTs, $\mathbf{V}_{rf} = [\mathbf{v}_1, \dots, \mathbf{v}_G] \in \mathbb{C}^{N_t \times G}$, and the baseband digital precoding matrix, which is normalized as $\mathbf{B}_d = \mathbf{B}_d / \sqrt{\|\mathbf{V}_{rf} \mathbf{B}_d\|_F} \in \mathbb{C}^{G \times G}$. The digital precoding is achieved by ZF precoding of the near UTs' effective channel matrix, $\mathbf{H}_e = \mathbf{H}_1^H \mathbf{V}_{rf}$ and it is defined as $\mathbf{B}_d = \mathbf{H}_e^H (\mathbf{H}_e \mathbf{H}_e^H)^{-1}$. In the presence of MC, the coupled channel gain of the near UTs in DL transmission, resulting from the hybrid beamforming is written by

$$\begin{aligned} \mathbf{U}_{MC}^{near} &= (\mathbf{C} \mathbf{H}_1)^H \mathbf{V}_{rf} \mathbf{B}_d \in \mathbb{C}^{G \times G}, \\ &= \mathbf{H}_1^H \mathbf{C}^H \mathbf{V}_{rf} \mathbf{H}_e^H (\mathbf{H}_e \mathbf{H}_e^H)^{-1}, \\ &= \mathbf{H}_1^H \mathbf{C}^H \mathbf{V}_{rf} \mathbf{V}_{rf}^H \mathbf{H}_1 (\mathbf{H}_1^H \mathbf{V}_{rf} \mathbf{V}_{rf}^H \mathbf{H}_1)^{-1}. \end{aligned} \quad (3.29)$$

Without considering the mutual coupling matrix $\mathbf{C}$, $\mathbf{U}_{MC}^{near}$ is a diagonal matrix, achieving zero inter-group inference between the groups. However, due the existence of the $\mathbf{C}$ matrix in (3.29), ZF based on the pre-beamforming channel is not valid, resulting in non-zero off diagonal matrix which is the inter-group inference.

3.2.2. Mutual coupling compensation

In the case, where mutual coupling is estimated perfectly and known at the BS, the modified beamforming/combining vectors can be defined as

$$\bar{\mathbf{v}} = (\mathbf{C}^H)^{-1} \mathbf{a}(\phi_1), \quad (3.30)$$

$$\bar{\mathbf{f}}^H = \mathbf{a}(\phi_1)^H \mathbf{C}^{-1}. \quad (3.31)$$

With mutual coupling compensated beamforming/combining vectors, the system sum-rate of the NOMA can be achieved without any loss. However, when the mutual coupling is unknown at the BS, different techniques can be applied to compensate for the mutual coupling effect. Here, the technique for MC compensation in [176], which was applied

to generate the compensated pattern, is briefly discussed. In general, when an antenna array is excited using a given voltage vector, $\mathbf{v}$, also known as a beamforming vector, the antenna array radiates and produces a radiation pattern. This radiation pattern is distorted due to the presence of MC between antenna array elements. In order to compensate, a new excitation vector $\mathbf{v}'$ is obtained using transmission line theory such that when the array is excited with these new voltages the radiation pattern becomes equal to the theoretical pattern that assumes no MC. This technique is not only simple but also non-invasive, i.e., no physical modification is required for the antenna array structure, and only the input voltages are changed.

Similarly, in the UL case, the received voltages at the terminals of the antenna array elements are observed. Due to the presence of MC, these received voltages are corrupted and thus results in loss of information such as in Direction Finding applications where the phase information is lost and needs to be recovered. Different techniques have been proposed for compensation in the receiving mode. A recent method in [177] for omnidirectional antennas suggests that by using a single decoupling matrix, any received voltage for all (θ, ϕ) directions can be decoupled. In other words, the mutual impedance matrix is not only constant for a given structure but is independent of the incident angle of the received signal and is only an inherent property of the structure alone. This method was further tested experimentally in [180] using Software Defined Radios (SDR). Thus, the mutual coupling compensation method in [177] was employed for the UL case.

3.2.3. Simulation setup

The simulation firstly considers the $K = 4$ -user single-group NOMA system, where they are located at $d = [100, 300, 500, 1000]$ m. Then, the NOMA system with $G = 4$ groups of users with $K = 2$ UTs in each group at $d = [500, 1000]$ m, is investigated. A dominant single path channel in (2.18) is applied at $f_c = 2.4$ GHz with the PL exponent $\eta = 2$. The system bandwidth is 1 MHz, and the noise power density is assumed to be $N_0 = -174$ dBm/Hz. There are three scenarios in the DL NOMA system, which are based on different array configurations; ULA, 2D-UCA, and 3D-UCA. Analog beamforming is applied in ULA and 2D-UCA cases for the single-group NOMA system, and hybrid beamforming is applied in 3D-UCA case for the multi-group NOMA system. In all scenarios, comparisons are performed for the effect of mutual coupling on the channel gains of all the UTs and

the total achievable sum-rate without MC, with MC compensation, and with unknown MC. Mutual coupling generation and compensation are implemented based on the induced EMF and MOM methods in all the results. The total achievable sum-rate is calculated as a summation of the sum-rate of both users; $R_1 + R_2$, and the sum-rate results are averaged over 1000 random runs. We consider a half-wavelength dipole antenna throughout the simulation. The details of the simulation parameters are listed in **Table 3.1**.

Table 3.1: Simulation parameters in NOMA system with MC.

Parameters	Value
Carrier frequency	$f_c = 2.4$ GHz
Bandwidth	1 MHz
Number of antenna at BS	ULA: $N_t = 16$ 2D-UCA : $N_t = 8$ 3D-UCA : $N_1 = 3, N_2 = 4$
Channel parameter	mmWave channel (2.18) with a single LOS path, $\eta = 2$
Noise power density	$N_0 = -174$ dbm/Hz
Number of UTs	Single group: $K = 4$ Multi-group: $G = 4, K = 2$ in each group
Distances	Single group: $d = [100, 300, 500, 1000]$ m Multi-group: $d = [500, 1000]$ m
Power allocation coefficients	Single group: $\gamma = [0.05, 0.15, 0.2, 0.6]$ Multi-group: $\gamma = [0.2, 0.8]$

3.3. Performance Analysis of User Scheduling in Massive MIMO with Fast Moving Users

In this section, performance analysis of user grouping and scheduling in a fast fading channel scenario, where the users are moving with the high speed, is investigated in multi-user scenario discussed in **Section 2.7**. A two-stage precoding technique proposed for FDD systems is adopted. This approach reduces the precoding transmit antenna size by suppressing the intra-group users with pre-beamforming matrix and inter-group users with precoding matrix separately [106]. Improved K-mean clustering methods with WLD similarity measure proposed in [109], [110] is considered as a user grouping method. As for the user scheduling within groups, two different methods: SUS algorithm [111] and greedy algorithm [109], [110] are employed.

The main objective of this work is to analyze how often the fast moving users are required

to be regrouped and rescheduled in fast fading channels by using the above-mentioned methods. In order to do so, users are first scheduled in a static channel for a one-time frame and then same scheduled users are considered for next time frames when the users start moving. In this way, how the system capacity changes with time can be observed in both scenarios: moving users with and without rescheduling.

3.3.1. Channel model with doppler effect

Predicted CSI is assumed to be known at the BS and the propagation channel is considered to be a mmWave channel. Due to the high free space path loss, the mmWave channel can be characterized by the geometric channel model composed of limited L scatterers for each user [38], [77]. In an environment, where users are moving with high velocity v , the channel changes with time t due to the Doppler shift. Assuming all users have the same number of scatterers, the block fading channel vector with Doppler effect between the BS antenna array and the moving user k can be formulated as,

$$\mathbf{h}_k(t) = \frac{\alpha}{PL_k} \sum_{l=1}^L \beta_{kl} e^{j2\pi f_D t} \mathbf{a}_k(\phi_l) \in \mathbb{C}^{N_t \times 1} \quad (3.32)$$

$f_D = f_m \cos(\theta_l^r)$ is the Doppler shift with maximum Doppler frequency $f_m = v/\lambda$ and the DoA θ_l^r of l^{th} path at the user. $\mathbf{a}_k(\phi_l)$ represents the normalized steering vector of the ULA array at DoD ϕ_l of the k^{th} user. It is known that the long-term channel statistics such as DoA, DoD and normalized average power of individual paths remain stationary over the transmission time [181], [182]. Thus, ignoring path loss, which is compensated by antenna gain operated at high frequency [183], channel covariance matrix of the user k can be obtained by using the long-term CSI as

$$\mathbf{R}_k = \mathbb{E} [\mathbf{h}_k \mathbf{h}_k^H] = \alpha^2 \sum_{l=1}^L \mathbf{a}_k(\phi_l) \mathbf{a}_k^H(\phi_l) \quad (3.33)$$

By using eigen-decomposition, the channel covariance matrix can be decomposed as $\mathbf{R}_k = \mathbf{U}_k \mathbf{\Lambda}_k \mathbf{U}_k^H$, with the unitary eigen matrix $\mathbf{U}_k$ and its diagonal matrix $\mathbf{\Lambda}_k$ consisting of the eigenvalues.

3.3.2. Simulation setup

A MIMO system with a ULA size of $N_t = 128$ and $d = 0.5\lambda$ antenna element spacing is assumed. The Doppler fast fading channels of moving users are based on Rayleigh

Jakes' channel model, which is generated from Gaussian noise filtered by Jakes' Doppler spectrum, and the carrier frequency is set at 60 GHz. $K = 100$ number of single-antenna users are uniformly placed around the BS in 120° sector with minimum distance $R_{min} = 20$ m, maximum distance $R_{max} = 200$ m and azimuth angles, $\phi_k = [-60^\circ, 60^\circ]$ from the BS. In addition, the number of scattered paths in a cluster is set as $L = 4$ and DoAs and DoAs are randomly extracted from Laplacian distribution with $\mu_k \sim \mathcal{U}[0, 2\pi]$ and $\sigma_s = 10^\circ$. Assuming the scatterers are stationary, the users are moving away or toward the BS with the random velocity ranging from $v = -20$ km/hr to $v = 40$ km/hr in horizontal-vertical velocity components. The maximum Doppler shift of each user varies according to the respective user velocity. The data sampling rate, f_s , is set as 100 MHz and the frame length is $T_{frame} = 6$ ms. The number of user groups is fixed at $G = 5$ with $r_g = 10$, thus $S = 50$ users are scheduled to be served out of K at a given time frame. The average system sum-rate curves are obtained from 500 channel realizations. In the static user environment, capacity curves of all K users, which are served simultaneously by only grouping, are also shown as a benchmark. The summary of the simulation set up is shown in **Table 3.2**.

Table 3.2: Simulation parameters in multi-user system with fast moving users.

Parameters	Value
Number of antennae	$N_t = 128$
Carrier Frequency	$f_c = 60$ GHz
User locations from BS	$R = [20, 200]$ m, $\phi_k = [-60^\circ, 60^\circ]$, Uniform
Number of total users	$K = 100$
Number of groups	$G = 5$
Number of selected users/group	$r_g = 10$
Speed of the users	$v_x = [-20, 40]$, $v_y = [-20, 40]$ km/hr
Frame Length	$T_{frame} = 6$ ms
Channel Model	Rayleigh Jakes' Model ($L = 4$)
Scheduling Algorithms	Greedy, SUS, Random

3.4. Low-Complexity Deep Learning-Based Beamforming in MISO Systems

The beamforming design problem has been an open issue in recent years, and many signal processing-based algorithms have been proposed to find the optimal solution. The conventional approaches are mostly iterative algorithms, which introduce high computational complexity. Therefore, in this chapter, a low-complexity DL-based beamforming

for a MISO system is proposed. A CNN model is employed due to its ability to share the same kernels between the first and second components and capture the local dependencies in the complex-valued input. Compared to the FCNN in [144], which introduces excessive parameters, making the model harder and more complex to train, CNN takes advantage of the shared kernels thus reduces the number of parameters. The main methodologies of this work are summarized as follows:

- A lesser complexity DL architecture based on the BFNN [144] is designed, by employing CNN.
- An interleaving-based input data arrangement, defined as Element-wise Successive Order Merging (ESOM), is proposed to consider both real and imaginary components of the input channel in the same convolution kernel.
- The impacts of different data representations, such as In-phase and Quadrature (IQ), Amplitude and Phase (A/Φ), and FFT, for the complex-valued input fed to the CNN model are compared.

3.4.1. System model

A downlink SU-MISO system is considered as shown in **Figure 3.2**, where a BS transmits a data symbol, s , to a single-antenna UT using one RF chain. The BS is assumed to be equipped with a ULA, consisting of N_t antenna elements, separated by r inter-element distance, which is typically a half of the transmission wavelength, λ . The transmitted

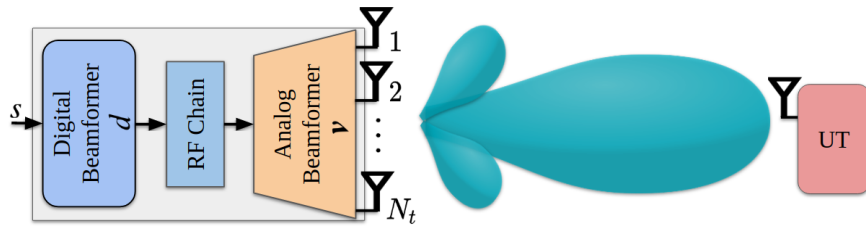


Figure 3.2: SU-MISO system with hybrid beamforming.

signal, $\mathbf{x} \in \mathbb{C}^{N_t \times 1}$ is expressed as $\mathbf{x} = \sqrt{P_t} \hat{\mathbf{v}} s$, where $\hat{\mathbf{v}} = \mathbf{v} / \sqrt{N_t} \in \mathbb{C}^{N_t \times 1}$ is a normalized AB vector that is obtained using PSs. The received signal at the user without interference, is given by $y = \mathbf{h}^H \sqrt{P_t / N_t} \mathbf{v} s + n$, where $n \sim \mathcal{CN}(0, \sigma_n^2)$ is the AWGN, and P_t is the total transmit power. In this single user case, $d = \sqrt{P_t / N_t}$ can be considered as a digital beamforming, which satisfies the total power constraint. The mmWave channel

between the BS and the user is designed using a geometric channel model with L limited scatterers and $\phi_l \sim \mathcal{U}[0, 2\pi]$ as discussed in **Chapter 2**.

3.4.2. Problem formulation

The spectral efficiency is formulated as $\text{SE} = \log_2 (1 + P_t |\mathbf{h}^H \mathbf{v}|^2 / (\sigma_n^2 N_t))$, considering PSSs' constant modulus constraint, i.e., $\|\mathbf{v}\| = \sqrt{N_t}$. The objective of the beamforming design is to maximize the system SE, in which the maximizing problem can be transformed into minimizing negative SE with the constant modulus constraint given as [144]

$$\begin{aligned} \underset{\mathbf{v}}{\text{minimize}} \quad & -\log_2 \left(1 + \frac{P_t |\mathbf{h}^H \mathbf{v}|^2}{\sigma_n^2 N_t} \right), \\ \text{subject to} \quad & |[\mathbf{v}]_k|^2 = 1, \forall k = 1, \dots, N_t. \end{aligned} \quad (3.34)$$

In the DL network, negative average SE across all training samples (N_s) is considered as a loss function ($\mathcal{L}$), given as

$$\mathcal{L} = -\frac{1}{N_s} \sum_{j=1}^{N_s} \log_2 \left(1 + \frac{\rho_j |\mathbf{h}_j^H \mathbf{v}_j|^2}{N_t} \right), \quad (3.35)$$

where $\rho_j = [P_t / \sigma_n^2]_j$ is the SNR value, $\mathbf{h}_j$ and $\mathbf{v}_j$ are the channel vector and the AB vector of the j^{th} training sample, respectively.

3.4.3. Proposed deep learning-based beamforming model

3.4.3.1. Data preparation

Since the input to the network, the imperfect CSI $\mathbf{h}_e$, is a complex-valued vector, it is required to transform the input to a real-valued vector in order to train the real-valued network. Moreover, it is a crucial task to find the right data representation, that is, the most discriminative features of the data in a specific problem [184]. Thus, the proposed network is trained for the same $\mathbf{h}_e$, represented in three different formats: IQ, A/ Φ , and FFT. In addition, in order to apply the same convolution kernels to both components of the channel coefficients and capture the local correlation between them, the components of the formatted channel are placed in order accordingly. For all N_t elements of the channel, the components of each channel element are arranged sequentially, in such a way that the first component is followed by the second component.

The k^{th} element of the formatted input channel coefficients with the new feeding arrangement can be represented as

$$\mathbf{h}_{e_k}^{A/\Phi} = \begin{bmatrix} h_{e_k}^A \\ h_{e_k}^\Phi \end{bmatrix}, \mathbf{h}_{e_k}^{IQ} = \begin{bmatrix} h_{e_k}^I \\ h_{e_k}^Q \end{bmatrix}, \mathbf{h}_{e_k}^{\mathcal{F}} = \begin{bmatrix} h_{e_k}^{Re} \\ h_{e_k}^{Im} \end{bmatrix}, \quad (3.36)$$

where $\mathbf{h}_{e_k}^{A/\Phi}$ consists of the amplitude and phase of the channel, $\mathbf{h}_{e_k}^{IQ}$ contains the in-phase (real) and quadrature (imaginary) time-domain channel components, and $\mathbf{h}_{e_k}^{\mathcal{F}}$ is comprised of the real and imaginary components of the frequency-domain channel. Then, concatenating $\forall k = 1, \dots, N_t$ elements of the transposed formatted channel, e.g. $\mathbf{h}_{e_k}^{IQ^T}$, forms the finalized input vector as $\mathbf{h}_e^{IQ} = [\mathbf{h}_{e_1}^{IQ^T}, \dots, \mathbf{h}_{e_{N_t}}^{IQ^T}]^T$, where $(\cdot)^T$ stands for transpose operator. The data formatting and arrangement in the input layer is depicted in **Figure 3.3**, where each complex-valued h_{e_k} is transformed into two real-valued components, $(h_{e_k}^{c1}, h_{e_k}^{c2})$, using one of the data representations. This is then followed by interleaving the formatted data as explained above. By applying the proposed data arrangement, the input vector has been turned into a more suitable form for the CNN model. This data arrangement format, for the remainder of the chapter, will be referred to as ESOM.

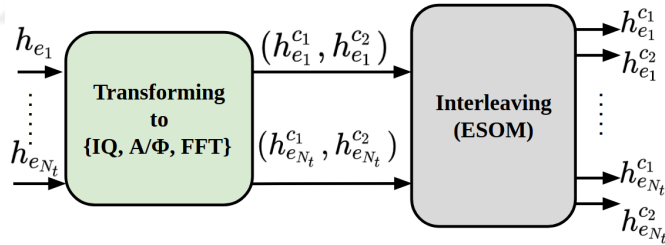


Figure 3.3: Data preparation: $h_{e_k}^{c1}$ and $h_{e_k}^{c2}$ are the first and second components of the k^{th} formatted input, h_{e_k} , for all k .

3.4.3.2. BFNN architecture

By exploiting the Convolutional Layer (CL)'s ability to learn with fewer parameters, a CNN-based model is constructed as shown in **Figure 3.4**. The proposed architecture achieves a similar SE as FCNN though it uses less than half of the number of FCNN parameters. The inputs are imperfect (estimated) and perfect channel vector, $\mathbf{h}_e$, $\mathbf{h}$; and a SNR value, ρ , for each sample. At the training stage, $\mathbf{h}_e$ are first pre-processed using one of the data representations discussed previously, and fed to the CNN unit for training, while $\mathbf{h}$ and ρ are fed to the Lambda Layer 2 for the loss calculation.

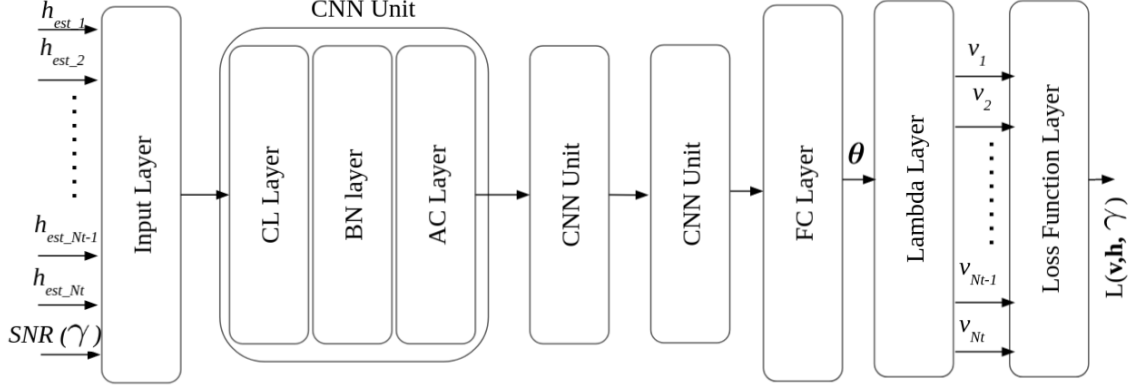


Figure 3.4: The proposed BFNN architecture.

Each CNN unit consists of 3 layers: CL, Batch Normalization (BN) layer, and Activation (AC) layer. The CL accepts the pre-processed $\mathbf{h}_e$ as a 1-D input vector. Each CL is composed of F number of kernels with the size $z \times 1$. The BN layer normalizes the output of the CL, which compensates for over-fitting and enables higher learning rate, thereby allowing acceleration of convergence. The AC layer contains an activation function, where Hyperbolic Tangent (Tanh) function is used to consider the negative outputs with nonlinearity. After passing all 3 CNN units, the 2-D output is converted into a 1-D vector using a Flatten Layer. Then, a FC layer is applied to the output of the Flatten Layer to generate the estimated phase vector $\boldsymbol{\theta}$ with size N_t . Lambda Layer 1, which transforms its input to a complex value, is included after the FC layer since it is required to transform the phase vector to a complex-valued beamforming vector, $\mathbf{v}$, with the constant modulus constraint as, $\mathbf{v} = \exp(j2\pi\boldsymbol{\theta})$, where $j = \sqrt{-1}$. Lastly, Lambda Layer 2, the loss function in (3.35), is applied using complex-valued $\mathbf{h}$, ρ , and $\mathbf{v}$ to achieve the robustness to the imperfect CSI, similar to the study in [144]. At the testing stage, using newly estimated $\mathbf{h}_e$ along with ρ and their respective trained weights, the optimized $\mathbf{v}_{opt}$ can be generated.

3.4.4. Simulation setup

A dataset, which was generated via MATLAB by the authors in [144], was utilized and can be found in [185]. The perfect channel coefficients were generated based on the channel model in (2.18), where $L = 3$. The simulation parameters of the generated channel based on [78] is summarized in Table 3.4. The imperfect channel was estimated using the pilot signals-based channel estimation technique in [78] at Pilot-to-Noise Power Ratio (PNR) =

Table 3.3: Hyper-parameters for CNN-BFNN model.

Layer	$d_o \times F_o$	z	AC	Number of Params.
Input Layer	128×1	-	-	0
Conv Layer 1	123×6	6	Tanh	42
BN Layer 1	123×6	-	-	24
Conv Layer 2	120×6	4	Tanh	150
BN Layer 2	120×6	-	-	24
Conv Layer 3	119×4	2	Tanh	52
BN Layer 3	119×4	-	-	16
Flatten Layer	476	-	-	0
FC Layer 1	64×1	-	Sigmoid	30528
Lambda Layer 1	64×1	-	-	0

0 dB and 20 dB. The detailed results for different values of PNR can be seen in [144]. The training dataset size is 100K samples with 10% of them as a validation set, and the testing dataset size is 10K samples. The training environment is based on Python 3.6 with TensorFlow 1.12.0 on 12 GB NVIDIA Tesla K80 graphics processing unit (GPU), provided by Google Colaboratory. Batch training was exploited with the batch size of 500 obtained by cross-validation. The training was initialized with the learning rate, $l_r = 10^{-3}$, then it was reduced until the minimum $l_r = 5 \times 10^{-5}$ by the factor of 0.2 after waiting for 20 epochs with no improvement. For the optimization method, Adaptive Moment (Adam) algorithm was used, and both networks were trained for 10K epochs. The detailed structures and the hyper-parameters for the proposed CNN model are given in **Table 3.3**.

Table 3.4: Simulation parameters of the dataset.

Parameters	Value
Carrier frequency	28 GHz
Bandwidth	100 MHz
Distance between BS and UT	$D = 50$ m, reference distance; $D_0 = 5$ m
Number of antenna at BS	ULA: $N_t = 64$
Channel parameter	$\beta_l \sim \mathcal{CN}(0, 1)$, $L = 3$
Average pathloss	$\gamma = \left(\frac{4\pi D_0}{\lambda}\right)^2 \left(\frac{D}{D_0}\right)^\eta$, $\eta = 3$

3.5. Joint Overlap Ratios And Power Allocation With User Fairness In Partial Non-Orthogonal Multiple Access (P-NOMA)

The main objective of this work is to obtain the optimum resource allocation parameters for P-NOMA system; ORs and power allocation coefficient, which maximize the total sum-rate while the desired user fairness is achieved. The proposed joint allocation algorithm is performed using gradient search method. In each step of the gradient search, power allocation coefficient is calculated under the constraint of Jain's fairness index [186]. The proposed algorithm also makes sure that the optimum sum-rate of the P-NOMA users is higher than that of the NOMA users. Compared the exhaustive search, the proposed gradient search method provides a lesser complexity with the same sum-rate performance.

3.5.1. Joint allocation of overlap ratios and power coefficient

In this section, joint allocation of ORs and power coefficient for the P-NOMA is investigated. The Jain's fairness index is adopted, which is defined as [186]

$$F = \frac{\left(\sum_{m=1}^M S_m\right)^2}{M \sum_{m=1}^M (S_m)^2}. \quad (3.37)$$

Jain's index varies between $1/M \leq F \leq 1$, where equal sum-rate, $S_n = S_f = S/2$, is achieved when $F = 1$, and one of the users occupies all sum-rate when $F = 1/2$, in two-user system. The objective is to maximize the total sum-rate, S , of the system with user fairness by adjusting the variables; α , β , and γ . Thus, the optimization problem is formulated as:

$$\underset{\alpha, \beta, \gamma}{\text{maximize}} \quad S = S_n + S_f \quad (3.38)$$

$$\text{subject to} \quad F \geq F_t; \quad (3.39)$$

$$0 \leq \gamma \leq \gamma_{max}; \quad (3.40)$$

$$S(\alpha, \beta, \gamma) \geq S_{NOMA, \gamma}; \quad (3.41)$$

where F_t is a target user fairness, and γ_{max} is the maximum power allocation coefficient for the near UT. In order to solve this allocation problem that results in the optimum solutions, $(\alpha_{opt}, \beta_{opt})$ and γ_{opt} , a gradient search-based algorithm is proposed, which achieve the maximum sum-rate with the given user fairness index, inspired by the algorithm in [187].

Given γ values with step size 0.02 and $\gamma_{max} = 0.3$, and $F_t = 0.7$ in this study, the optimum sum-rate, S_{opt} , is first initialized as zero, and the resolution of (α, β) as $\Delta = 0.1$. The algorithm is started with $(\alpha, \beta) = (1, 1)$ in order to ensure that the optimum sum-rate is higher than that of the conventional NOMA, S_{NOMA} . From the sum-rate graph with the fairness constraint, shown in **Figure 4.20a**, which was obtained using exhaustive search, it is observed that the sum-rate function with respect to different ratio pairs (α, β) is an increasing function with a maximum point, increasing toward the direction of decreased ORs. Thus, the sum-rate of the current (α, β) is compared with those of the next sets of the ratios, $(\alpha^* = \alpha - \Delta, \beta)$ and $(\alpha, \beta^* = \beta - \Delta)$. If the gradients (differences) between the current ratios and the next ratios sets are positive, the current ratios are moved to the next ratios that have the higher gradients, and the S_{opt} is updated. If the gradients are negative, then the current Δ is increased by 0.1, and the next sets of ratios are obtained. The process is repeated until one of the next ratios becomes 0. Given different power allocation coefficients, for any (α, β) , the sum-rate S is optimized under Jain's fairness as follows. S and Jain's index, F , with respect to all γ values are calculated first. Next, the sum-rate with $F < F_t$ is assigned to zero. Then, the maximum sum-rate is chosen, along with its index, i_{opt} , that is used to allocate the sub-optimum $\gamma(i_{opt})$ and $F(i_{opt})$.

The details of the proposed algorithm is described in **Algorithm 3.3**. The complexity of the exhaustive search is $\mathcal{O}((1/\Delta)^2)$, considering all possible pairs of the ORs, where $\mathcal{O}(\cdot)$ denotes big-O notation [160]. In contrast, the proposed algorithm has two pairs of (α, β) comparison in **Step 2**), repeated for $1/\Delta$ number of next ratios if the next ratios do not provide positive gradients. Hence, it results in $2/\Delta$ comparison pairs. If the current ratios are updated for n -times until the optimum solutions are found, the total complexity of the proposed algorithm is $\mathcal{O}(2n/\Delta)$, which is much less than the exhaustive search.

3.5.2. Simulation setup

The simulations were performed in $M = 2$ single-antenna users system, and $N_t = 512$ with $\Delta_{sub} = 15$ kHz. A perfect SIC is considered at near user, i.e. $\delta = 0$, and the SNR per subcarrier is $SNR_k = 10$ dB with $\sigma_k^2 = 0$ dB. The channel is composed of i.i.d. Rayleigh fading with zero mean and unit variance, and path loss with exponent factor 4. The summary of the simulation set up is shown in **Table 3.5**.

Algorithm 3.3: Proposed Gradient Search-Based Joint Allocation

- 1: **Given:** $\gamma = 0$ to $\gamma_{max} = 0.3$ with step 0.02 and F_t .
 - 2: **Initialization:** $S_{opt} = 0$, $\Delta = 0.1$, $(\alpha, \beta) = (1, 1)$.
 - 3: **Step 1):** Update the values $\alpha^* = \alpha - \Delta$ and $\beta^* = \beta - \Delta$.
 - 4: Calculate $S(\alpha, \beta)$, $S(\alpha^*, \beta)$, and $S(\alpha, \beta^*)$ in **Step 1. a)**.
 - 5: **Step 1. a):** $\forall \gamma$, calculate S in (3.38) and F in (3.37).
 - 6: Find all the indices of γ at $F < F_t$; i , and $S(i) = 0, \forall i$.
 - 7: Find the maximum S and its index i_{opt} .
 - 8: Thus, for any (α, β) , $S = S(i_{opt})$, $\gamma = \gamma(i_{opt})$, and $F = F(i_{opt})$ are calculated for **Step 1).**
 - 9: **Step 2):** Find the gradients: $G_{\alpha^*} = S(\alpha^*, \beta) - S(\alpha, \beta)$ and $G_{\beta^*} = S(\alpha, \beta^*) - S(\alpha, \beta)$.
 - 10: **if** $G_{\beta^*} > 0$ & $G_{\alpha^*} > 0$ **then**
 - 11: **Update:** the current (α, β) as follow:
 - 12: **if** $G_{\beta^*} > G_{\alpha^*}$ **then**
 - 13: $\alpha = \alpha$ and $\beta = \beta^*$
 - 14: **else**
 - 15: $\alpha = \alpha^*$ and $\beta = \beta$
 - 16: **end if**
 - 17: Save the updated current (α, β) in $(\alpha_{opt}, \beta_{opt})$, update $S_{opt} = S(\alpha, \beta)$, and let $\Delta = 0.1$.
 - 18: **else**
 - 19: No updating the current (α, β) , and $S_{opt} = S(\alpha, \beta)$.
 - 20: Update $\Delta = \Delta + 0.1$ and repeat the process from **Step 1)** until $\alpha = 0$ or $\beta = 0$.
 - 21: **end if**
 - 22: **if** $\alpha = 0$ or $\beta = 0$ **then**
 - 23: **Stop:** the process, and the optimum $(\alpha_{opt}, \beta_{opt})$, S_{opt} , and $\gamma(\alpha_{opt}, \beta_{opt})$ are obtained.
 - 24: **end if**
-

3.6. Partial-Beam Non-Orthogonal Multiple Access (PB-NOMA) with Fuzzy Clustering

In this section, a PB-NOMA system is proposed, where the UTs which partially belong to different groups that undergo power-domain NOMA technique in the available spectrum bandwidth. FCM clustering is proposed to cluster the UTs in order to group the users who can partially belong to more than one group. The main objective of this study is to investigate how the OBRs affect the sum-rates of the near and far UTs in the proposed model. This section also elaborates on the FCM clustering with a suitable similarity measure and user pairing based on the required condition of the system.

Table 3.5: Simulation parameters in P-NOMA system.

Parameters	Value
Number of subcarriers	$N = 512$
Subcarrier spacing	$\Delta_{sub} = 15$ kHz
Number of UTs	$M = 2$
Perfect SIC	$\delta = 0$
Channel parameter	$\beta_l \sim \mathcal{CN}(0, 1), \eta = 4$
Distance Ratio	1 : 2
SNR per subcarrier	$SNR_k = 10$ dB
Jain's Index	0.7, 0.9

3.6.1. Proposed partial-beam NOMA system

In this section, a basic structure of the proposed PB-NOMA system is discussed and the achievable sum-rate of the system is derived. A downlink system with a BS, consisting of an N_t -sized ULA and K number of single-antenna UTs, is considered. Unlike conventional NOMA systems, the proposed PB-NOMA system assumes that some UTs belong to more than one user group.

A simple scenario of the proposed system is depicted in **Figure 3.5**, where UTs are assumed to be closely overlapped and clustered into $G = 2$ groups. At the same frequency and time, each g^{th} group is served by the respective beam generated using a beamforming vector $\mathbf{w}_g$, and two UTs in each group are selected for a typical P-NOMA scheme (see details in [47]). In addition, the UTs in the overlapped beam region are also proposed to be accommodated with P-NOMA by adjusting the OBRs $\epsilon_g, \forall g \in \{1, 2\}$. **Figure 3.5** also

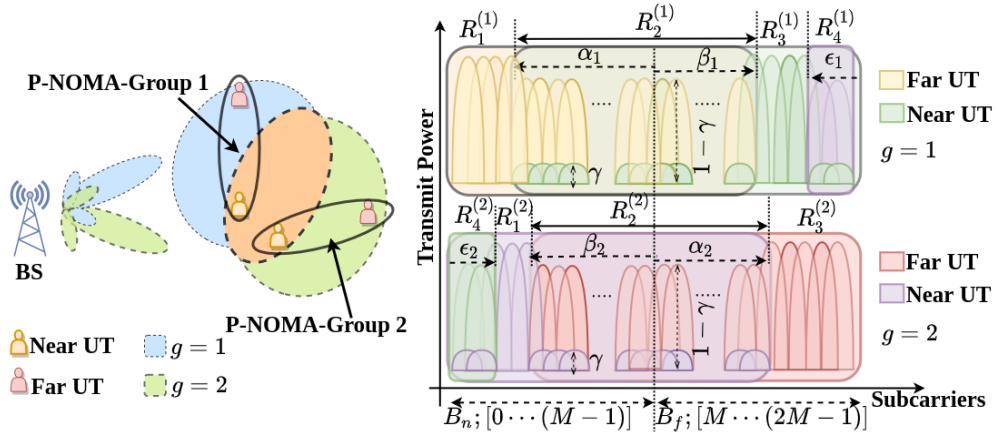


Figure 3.5: Partial-beam NOMA system model with overlapped clusters, where near UTs in group 1 and group 2 partially belong to each other's group.

shows the signal model for two groups of users. They occupy a bandwidth of $B_n + B_f$, and each signal is transmitted to the targeted group with the help of beamforming, i.e., spatially. $u_{1,n}$ and $u_{2,n}$ are assumed to be the overlapped beam near UTs of group 1 and 2, respectively. In each g^{th} group, the regions, $R_1^{(g)}$ and $R_3^{(g)}$, are the non-overlapping regions, to which OMA scheme is applied. In $R_2^{(g)}$ region, NOMA scheme is implemented using different Power Allocation (PA) coefficients, in which γ and $1 - \gamma$ are the PA coefficients of the near and far UTs, respectively. In addition, the overlapped beam UTs also apply NOMA scheme in $R_4^{(g)}$.

Assuming M number of subcarriers for each UT in g^{th} group with NOR α_g and FOR β_g , the non-overlapping regions in group $g = 1$, $R_1^{(1)}$ and $R_3^{(1)}$, are defined as $0 \leq m \leq M - \lfloor \alpha_1 M \rfloor - 1$ and $M + \lfloor \beta_1 M \rfloor \leq m \leq 2M - \lfloor \epsilon_1 M \rfloor - 1$, respectively. In group $g = 2$, $R_1^{(2)}$ is $\lfloor \epsilon_2 M \rfloor \leq m \leq M - \lfloor \beta_2 M \rfloor - 1$, and $R_3^{(2)}$ is $M + \lfloor \alpha_2 M \rfloor \leq m \leq 2M - 1$. The overlapping regions in both groups, $R_2^{(1)}$ and $R_2^{(2)}$, are given as $M - \lfloor \alpha_1 M \rfloor \leq m \leq M + \lfloor \beta_1 M \rfloor - 1$, and $M - \lfloor \beta_2 M \rfloor \leq m \leq M + \lfloor \alpha_2 M \rfloor - 1$, respectively. In addition, the overlapped beam regions are $R_4^{(1)}$, $2M - \lfloor \epsilon_1 M \rfloor \leq m \leq 2M - 1$, and $R_4^{(2)}$, $0 \leq m \leq \lfloor \epsilon_2 M \rfloor - 1$. ϵ_g varies according to β_g in the respective group g . Thus, ϵ_g is bounded as $0 \leq \epsilon_g \leq 1 - \beta_g$ that makes the total OR $0 \leq \epsilon_g + \beta_g \leq 1$, excluding the NOR, $0 \leq \alpha_g \leq 1$.

At m^{th} subcarrier, the SINRs of the non-overlapped beam UTs $\forall g \in \{1, 2\}$ are derived as

$$SINR_{g,f}[m] = \begin{cases} \frac{P_{gf}[m]}{\hat{P}_{gf}[m] + \sigma_m^2}, & m \in \{R_1^{(1)}, R_3^{(2)}\}, \\ \frac{(1-\gamma)P_{gf}[m]}{\gamma P_{gf}[m] + \hat{P}_{gf}[m] + \sigma_m^2}, & m \in \{R_2^{(1)}, R_2^{(2)}\}, \end{cases} \quad (3.42)$$

$$SINR_{g,n}[m] = \begin{cases} \frac{P_{gn}[m]}{\hat{P}_{gn}[m] + \sigma_m^2}, & m \in \{R_3^{(1)}, R_1^{(2)}\}, \\ \frac{\gamma P_{gn}[m]}{\delta(1-\gamma)P_{gn}[m] + \hat{P}_{gn}[m] + \sigma_m^2}, & m \in \{R_2^{(1)}, R_2^{(2)}\}, \end{cases} \quad (3.43)$$

where $P_{gf(n)}[m] = |\mathbf{H}_{g,f(n)}^H[m]\mathbf{w}_g|^2 P_m$ and $\hat{P}_{gf(n)}[m] = |\mathbf{H}_{g,f(n)}^H[m]\mathbf{w}_{g' \neq g}|^2 P_m$ are the channel gains with transmit power P_m at the main beam and the side beam (inter-group interference) at the far (or near) UT, respectively. σ_m^2 and $P_m = P_t/G(2M)$ are the noise variance and the allocated power at m^{th} subcarrier of the g^{th} group, respectively, with P_t being the total transmit power of the BS. $0 \leq \delta \leq 1$ denotes the SIC effect. On the other

hand, SINRs at the overlapped beam UTs, $u_{1,n}$ and $u_{2,n}$, are derived as

$$SINR_{1,n}[m] = \begin{cases} \frac{\gamma P_{1n}[m]}{\delta(1-\gamma)P_{1n}[m] + \hat{P}_{1n}[m] + \sigma_m^2}, & m \in \{R_4^{(1)}\}, \\ \frac{(1-\gamma)\hat{P}_{1n}[m]}{\hat{I}_1 + I_1 + \sigma_m^2}, & m \in \{R_4^{(2)}\}, \end{cases} \quad (3.44)$$

$$SINR_{2,n}[m] = \begin{cases} \frac{(1-\gamma)P_{2n}[m]}{\hat{I}_2 + I_2 + \sigma_m^2}, & m \in \{R_4^{(1)}\}, \\ \frac{\gamma P_{2n}[m]}{\delta(1-\gamma)P_{2n}[m] + \hat{P}_{2n}[m] + \sigma_m^2}, & m \in \{R_4^{(2)}\}, \end{cases} \quad (3.45)$$

where $\hat{I}_g = \gamma \hat{P}_{gn}[m]$, $\forall g \in \{1, 2\}$ are the intra-group NOMA interference in the side-lobe beam, and $\hat{I}_g = \gamma \hat{P}_{gn}[m]$, $\forall g \in \{1, 2\}$ are the intra-group interference from the far UTs with OMA scheme in its own group.

It is worth mentioning that in the overlapped beam region, e.g. $R_4^{(2)}$, where $u_{1,n}$ occupies the additional $\lfloor \epsilon_2 M \rfloor$ subcarriers from $u_{2,n}$ by applying NOMA, $u_{1,n}$ utilizes the side-lobe beam of the group 2, which is leaking toward the direction of $u_{1,n}$. This is because they both are in different groups with their respective beams. In this case, assuming the beams generate the same gain, NOMA scheme cannot be applied to different beams since the SIC is not effective at the receiver. However, if the BS still tries to apply the NOMA scheme, unnecessary interference can occur as the users have already been spatially separated by beamforming. Additionally, it can be noticed in (3.44) and (3.45) that in the overlapped beam regions, the power of the desired received signal is allocated by higher PA coefficient, $1 - \gamma$. This is due to the fact that low power of the side-lobe beam makes a near UT to be regarded as a far UT.

With the proposed PB-NOMA, the occupied bandwidths of the far and near UTs in group g , given the subcarrier spacing Δ_s , is obtained as $B_{g,f} = \Delta_s(M + \lfloor \beta_g M \rfloor)$, and $B_{g,n} = \Delta_s(M + \lfloor \alpha_g M \rfloor + \lfloor \epsilon_{g' \neq g} M \rfloor)$. Thus, the achievable sum-rate of the far and near UTs can

be calculated as

$$S_{1,f} = \Delta_s \sum_{m \in \{R_1^{(1)}, R_2^{(1)}\}} \log_2(1 + SINR_{1,f}[m]), \quad (3.46)$$

$$S_{1,n} = \Delta_s \sum_{m \in \{R_2^{(1)}, R_3^{(1)}, R_4^{(1)}, R_4^{(2)}\}} \log_2(1 + SINR_{1,n}[m]), \quad (3.47)$$

$$S_{2,n} = \Delta_s \sum_{m \in \{R_4^{(1)}, R_4^{(2)}, R_1^{(2)}, R_2^{(2)}\}} \log_2(1 + SINR_{2,n}[m]), \quad (3.48)$$

$$S_{2,f} = \Delta_s \sum_{m \in \{R_2^{(2)}, R_3^{(2)}\}} \log_2(1 + SINR_{2,f}[m]). \quad (3.49)$$

In this study, a hybrid beamforming scheme is employed where MRT is considered as an analog beamformer. As for the digital precoder, eigen-beamforming is exploited. The MRT is applied based on the weighted channel of the near UTs which are averaged over subcarriers. Since near UTs share a similar channel condition, it is proposed to formulate the weighted channel of the near UTs at m^{th} subcarrier as $\hat{\mathbf{H}}_{g,n}[m] = b_g \mathbf{H}_{g,n}[m] + (1 - b_g) \mathbf{H}_{g',n}[m]$, where b_g is the membership value of the near UT in group g . After obtaining the analog beamformer, eigen-beamforming is performed based on the effective channel of each subcarrier.

3.6.2. Sum-rate comparison between P-NOMA and PB-NOMA

Assuming that all the subcarriers are allocated with the same power and have similar channel gains due to mmWave channel characteristic, i.e., $P_m = P$ and $P_{g,f(n)}[m] \approx P_{g,f(n)} \forall m$, in P-NOMA system [47], the total achievable sum-rates of the far (or near) UT at group g for an allocated bandwidth with any given α_g and β_g can be obtained as (3.50) and (3.51), respectively. Considering perfect SIC, i.e., $\delta = 0$ at the near users, the first terms in both equations are the total sum-rates of OMA, while the second terms are that of NOMA system. Then, the total sum-rate of P-NOMA at group g is given as $S'_g = S'_{g,n} + S'_{g,f}$.

$$S'_{g,n} \approx \Delta_s M(1 - \beta) \log_2 \left(1 + \frac{P_{g,n}}{\hat{P}_{g,n} + \sigma^2} \right) + \Delta_s M(\alpha_g + \beta) \log_2 \left(1 + \frac{\gamma P_{g,n}}{\hat{P}_{g,n} + \sigma^2} \right). \quad (3.50)$$

$$S'_{g,f} \approx \Delta_s M(1 - \alpha_g) \log_2 \left(1 + \frac{P_{gf}}{\hat{P}_{gf} + \sigma^2} \right) + \Delta_s M(\alpha_g + \beta) \log_2 \left(1 + \frac{(1 - \gamma)P_{gf}}{\gamma P_{gf} + \hat{P}_{gf} + \sigma^2} \right). \quad (3.51)$$

On the other hand, in the proposed PB-NOMA system, the bandwidth of the near UT in group g' can be allocated to increase the near UT's sum-rate of group g instead of utilizing more bandwidth of the far UT in the same group g . Thus, a new reduced $\hat{\alpha}_g = \alpha_g - \epsilon_{g'}$ can be used as NOR. Consequently, the total achievable sum-rates of the proposed system with the given OBR $\epsilon_{g'}$ is obtained as (3.52) that is proved in **Appendix A.1**. Compared to P-NOMA, the sum-rates of the proposed system include the additional terms which contribute the sum-rate gain of both far and near UTs in group g since $O_f > N_f$. However, there is a sum-rate loss of the near UTs in the other group g' . Thus, the proposed scheme has an advantage in increasing the sum-rate of the near UTs without sacrificing the resource of its far UTs in the respective group.

$$S_g \approx S'_g + \Delta_s M \epsilon_{g'} \left[\underbrace{\log_2 \left(1 + \frac{P_{gf}}{\hat{P}_{gf} + \sigma^2} \right)}_{O_f} - \underbrace{\log_2 \left(1 + \frac{(1 - \gamma)P_{gf}}{\gamma P_{gf} + \hat{P}_{gf} + \sigma^2} \right)}_{N_f} + \underbrace{\log_2 \left(1 + \frac{(1 - \gamma)\hat{P}_{gn}}{\gamma \hat{P}_{gn} + P_{gn} + 1} \right)}_E - \underbrace{\log_2 \left(1 + \frac{P_{g'n}}{\hat{P}_{g'n} + \sigma^2} \right)}_{O'_n} \right]. \quad (3.52)$$

3.6.3. User clustering and pairing

In this section, clustering and user pairing algorithms suitable for the proposed PB-NOMA system are described. Since the user clustering and pairing algorithm based on channel correlation and gain difference in [45] is a hard clustering, it is not suitable for the case where there exists overlapped users. Therefore, in this study, fuzzy soft clustering is performed first, followed by user pairing which is based on the fuzzy membership and channel gain difference.

3.6.3.1. Fuzzy user clustering

Fuzzy clustering groups the users by comparing the membership of the users to each cluster head, based on the similarity between them [188]. The higher the similarity, the higher

its membership in the group of the cluster head. Unlike [188] which utilizes distance as a similarity measure, in this study, it is proposed to consider a channel correlation coefficient, $0 \leq |\rho| \leq 1$, as a similarity measure so that beamforming gain based on the channel condition of one user can be applied almost equally to all users in the same group, contributing an increase in sum-rate. Though channel correlation is also used in [45], [65], it requires a predetermined correlation threshold for hard clustering, while in this work soft clustering is performed without the correlation threshold. Since each UT carries information on channel subcarriers, the correlation coefficients are calculated based on the average frequency domain channel vector, $\mathbf{H}_{a_k} = \sum_{m=1}^{2M} \mathbf{H}_k[m]/(2M) \in \mathcal{C}^{N_t \times 1}$. The channel correlation coefficient between any i^{th} and j^{th} UTs can be obtained as $C_{i,j} = \frac{|\mathbf{H}_{a_i}^H \mathbf{H}_{a_j}|}{\|\mathbf{H}_{a_i}\| \|\mathbf{H}_{a_j}\|}$. Then, a decorrelation coefficient can be calculated as $l_{i,j} = 1 - C_{i,j}$. The details of the FCM clustering algorithm are summarized in **Algorithm 3.4**.

Algorithm 3.4: Proposed Fuzzy C-Means Clustering with Channel Correlation

- 1: **Initialization:** Randomly generate a membership matrix $\mathbf{F} \in \mathcal{R}^{G \times K}$, where summation of each column is 1.
- 2: **Updating Cluster Head:** Update the cluster head $\forall g$ as

$$\mathbf{H}_{a_g} = \frac{\sum_{k=1}^K \mathbf{H}_{a_k} \mathbf{F}_{k,g}^f}{\sum_{k=1}^K \mathbf{F}_{k,g}^f}, \quad (f \text{ is the fuzziness index}). \quad (3.53)$$

- 3: **Similarity Calculation:** In each group, calculate $C_{g,\forall k}$ between the cluster head g and all K number of UTs.
- 4: **Updating Membership:** Update $\mathbf{F}$ as (3.54), where $\mathbf{L} = [\mathbf{l}_1^T, \dots, \mathbf{l}_G^T]^T \in \mathcal{R}^{G \times K}$, $\mathbf{l}_g = \mathbf{1} - C_{g,\forall k} \in \mathcal{R}^{1 \times K}$.

$$\mathbf{F} = \frac{\mathbf{L}^{-\frac{1}{f-1}}}{\mathbf{e} \sum_{g=1}^G \mathbf{l}_g^{-\frac{1}{f-1}}}, \quad \mathbf{e} = \mathbf{1} \in \mathcal{R}^{G \times 1}. \quad (3.54)$$

- 5: Repeat the Step 2 through 4 until the total dissimilarity in (3.55) satisfies the objective function as $|J(t) - J(t-1)| \leq \zeta$, or maximum number of iterations, t , is reached.

$$J(t) = \mathbf{e}^T (\mathbf{L} \odot \mathbf{F}^f) \mathbf{a}, \quad \mathbf{a} = \mathbf{1} \in \mathcal{R}^{K \times 1}. \quad (3.55)$$

- 6: **Grouping:** Group all UTs that have the maximum membership value in their respective group.
-

3.6.3.2. User pairing

In [45], user pairing depends on the channel gain difference while satisfying a predetermined correlation threshold. In this study, the channel gain difference which satisfies the membership values of the users in both groups is considered. There are two conditions to be considered in user pairing: fuzzy membership values and channel gain difference. Firstly, since near UTs in the overlapped beam regions utilize the side-lobe beam of the user group that is not their groups, the membership value of the near UTs that corresponds to the other group should be big enough to achieve high correlation with that group. Similarly, the F value of the far UTs should be large enough to achieve high correlation (e.g. $|\rho| \approx 0.7$) with the near UTs in their own groups. Secondly, in order to perform perfect SIC, i.e. $\delta = 0$, at the near UT, the received power difference between the UTs must be large. This can be achieved if the channel gain difference between the UTs is high. Based on these criteria, a pair of UTs, $(u_{g,n}, u_{g,f})$, in each clustered group g is selected as outlined in **Algorithm 3.5**.

Algorithm 3.5: Proposed User Pairing Scheme

- 1: **Initialization:** $\forall g$, collect the F values of all K_g number of clustered UTs as $\mathbf{F}_{g' \neq g, k_g}^{(g)} \forall k_g \in \{1, \dots, K_g\}$. Then, calculate the channel gain difference based on the average frequency channel gain $H_{dij} = ||\mathbf{H}_{ai}||^2 - ||\mathbf{H}_{aj}||^2$. Let the maximum channel gain difference be $H_{dmx} = 0$.
 - 2: **User pairing under conditions:** When $H_{dij} \geq 0$, $||\mathbf{H}_{ai}||^2$ is the near UT channel gain. The boundary of the membership are chosen as $\mathbf{F}_{g' \neq g, i}^{(g)} \geq 0.4$ and $0.2 \leq \mathbf{F}_{g' \neq g, j}^{(g)} \leq 0.4$. If these conditions are true and $|H_{dij}| \geq H_{dmx}$, $H_{dmx} = |H_{dij}|$, then (i, j) is the updated pairs of the group g .
 - 3: **Repetition:** Repeat Step 2. until $|H_{dij}| \leq H_{dmx} \forall g$.
-

3.6.4. Simulation setup

The BS is equipped with $N_t = 16$ antennae at the carrier frequency $f_c = 28$ GHz. A mmWave channel [65] is considered with one LOS with path-loss exponent $\eta = 4$ and $L = 2$ non-LOS paths. The UTs are distributed based on a Poisson cluster process (PCP) model, where a group of children users is generated under Poisson distribution in a disc with radius 2 m around each parent user that follows uniform distribution in a 45° sector of a disc with radius 4 m. The number of subcarriers is $M = 512$ with $\Delta_s = 120$ kHz. In order to cluster the users that belong to both groups, a reasonably higher value, $f = 2$, is

chosen since it is known that the fuzzy clustered users with smaller $f \approx 1$ become similar to those of hard clustering. Threshold for clustering is set at $\zeta = 10^{-5}$, and lower PA coefficient, $\gamma = 0.1$, is allocated for a perfect SIC NOMA system. The clustering and user pairing are performed using the proposed algorithm for one time, and the selected users are fixed throughout the simulations. The summary of the simulation set up is shown in **Table 3.6**.

Table 3.6: Simulation parameters in PB-NOMA system.

Parameters	Value
Carrier frequency	$f_c = 28$ GHz
Number of antenna at BS	ULA $N_t = 16$
Number of subcarriers	$M = 512$ per UT in each group
Subcarrier spacing	$\Delta_s = 15$ kHz
NOMA parameters	$\delta = 0, \gamma = 0.1$
FCM clustering parameters	$f = 2, \zeta = 10^{-5}$
Channel parameters	NLOS ($L = 2$)+ LOS ($L = 1$): $\eta = 4$.
User distribution:	Poisson cluster process (PCP) model
SNR per subcarrier	$P_m = 10$ dB, $\sigma_m^2 = -2$ dB
Hybrid beamforming	Analog: MRT; Digital: Eigen-beamforming

3.7. Outage Probability Analysis Of Reconfigurable Intelligent Surface-Enabled Coordinated Multi-points NOMA Networks

In this section, RIS is proposed to be employed at one of the cell-edge UTs in the JT-CoMP-NOMA networks in order to increase its channel gain. The proposed network model consists of two overlapped cells, two RISs, and five UTs, where two cell-edge UTs are JT-CoMP users and one cell-edge UT in each cell are non-JT-CoMP user. RIS in each cell is located near the targeted cell-edge UT, and the phase-shifts of the RIS elements are designed to direct the reflected signals toward only that cell-edge UT. The main objective of this study is to analyse the performance of the proposed system in terms of outage probability analysis. Thus, the exact OP expression of each UT is firstly derived based on their channel statistics of i) traditional JT-CoMP NOMA system, ii) JT-CoMP NOMA system with reflected path, and iii) JT-CoMP NOMA system with both direct and reflected paths. In addition, the upper-bound OP of the proposed system based on the worst-case channel gain is also shown. The OP performance comparison of the proposed system in the different scenarios are then discussed along with their analytical results.

3.7.1. System model

A RIS-assisted downlink NOMA system in a JT-CoMP network is considered as shown in **Figure 3.6**. The proposed JT-CoMP network consists of two cells where the cell-edge UTs are the JT-CoMP users. Using NOMA scheme, the BS in each i^{th} cell transmits a superimposed signal to two cell-edge UTs, U_1 and U_2 , and a cell-center UT, $U_{3,i}$,

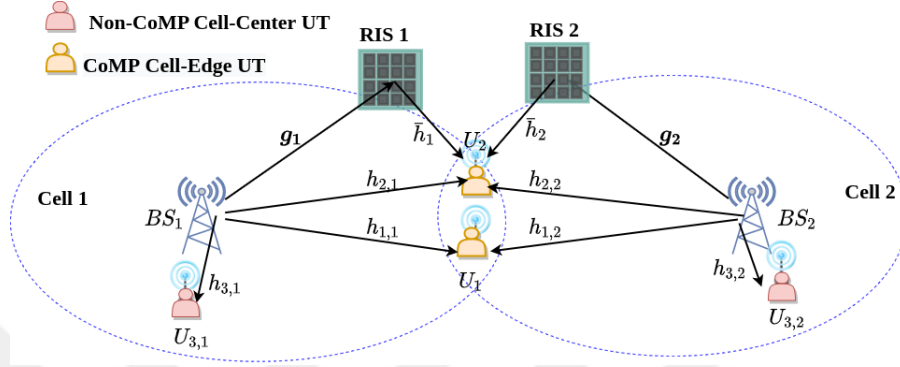


Figure 3.6: RIS-enabled CoMP-NOMA system model.

Though a multi-antenna system is also possible, for the sake of simplicity, both BSs and UTs are equipped with a single antenna and each RIS has M reflecting elements. The distances between the BS and the cell-edge UTs are the same so that at these UTs imperfect SIC case is created. Therefore, in order to increase the channel gain of U_2 only, in the proposed system, a RIS is employed near to the U_2 in each cell. The additional paths from the RISs provide more diversity and stronger channel gains for U_2 compared to U_1 that can only receive signals in the direct paths from the BSs.

The channel coefficient of the direct path between i^{th} BS and k^{th} UT is denoted as $h_{k,i} \in \mathbb{C}$. The channel vector between BS and the RIS in i^{th} cell is $\mathbf{g}_i \in \mathbb{C}^{M \times 1}$, and that between the RIS and the U_2 is $\bar{\mathbf{h}}_i \in \mathbb{C}^{M \times 1}$. The channel coefficients in all paths are assumed to be the complex Gaussian Random Variable (RV)s with mean 0 and variance σ_c^2 , i.e., $\mathcal{CN}(0, \sigma_c^2)$, where $\sigma_c^2 \in \{d_{k,i}^{-\eta_a}, d_{b,i}^{-\eta_b}, d_{r,i}^{-\eta_c}\}$ are the path-loss of both direct paths and the RIS paths based on the distances between BS i and U_k ; $d_{k,i}$, BS i and RIS i ; $d_{b,i}$, RIS i and U_2 ; $d_{r,i}$, and their path-loss exponents $\eta_l, l \in \{a, b, c\}$.

Considering the reflected path from the RIS, the effective channel of U_2 is expressed as $\hat{h}_{2,i} = \bar{\mathbf{h}}_i^H \mathbf{\Theta}_i \mathbf{g}_i + h_{2,i}$, where $\mathbf{\Theta}_i \in \mathbb{C}^{M \times M}$ is a diagonal matrix composed of $\beta_m e^{j\theta_m}, \forall m = 1, \dots, M$ as the diagonal elements, where β_m and θ_m are the amplitude reflection coefficient and reflection phase-shift at i^{th} RIS, respectively. The amplitude

reflection coefficients are assumed to be fixed i.e., $\beta_m = 1, \forall m$. Both direct path and BS-RIS-UT paths are considered to be known at the respective RIS in each cell. Then, the reflection phase-shift can be calculated such that the reflected path is only directed toward the U_2 and maximize the channel gain at the U_2 . The RIS effective channel of U_2 can be rewritten as $\hat{h}_{2,i} = \sum_{m=1}^M |\bar{h}_{i_m}| |g_{i_m}| e^{j(\theta_{h_m}^i + \theta_{g_m}^i + \theta_m^i)} + |h_{2,i}| e^{j\theta_{2,i}^i}$, where θ^i 's are the phases of the respective channel coefficients at each cell i . The channel gain is maximum when the RIS path and the direct path are co-phased [166]; $\theta_{h_m}^i + \theta_{g_m}^i + \theta_m^i = \theta_{2,i}^i$, hence the reflection phase-shift θ_m can be obtained as $\theta_m^i = \theta_{2,i}^i - (\theta_{h_m}^i + \theta_{g_m}^i)$. Thanks to RIS, the channel gains of the cell-edge UTs can be distinguished even though they are located at the same distance from the BS, thus SIC decoding scheme can be performed successfully based on the channel gain order $|\hat{h}_{1,i}|^2 < |\hat{h}_{2,i}|^2 < |\hat{h}_{3,i}|^2$, where $\hat{h}_{2,i} = h_{2,i}$, and $\hat{h}_{3,i} = h_{3,i}$.

3.7.2. Signal model

Assuming both BSs have the same total transmit power, P_t , and power allocation coefficient α_k , the transmitted signal at the i^{th} BS is given as

$$x^{(i)} = \sum_{k=1}^2 \sqrt{\alpha_k P_t} s_k + \sqrt{\alpha_3 P_t} s_{3,i}, \quad (3.56)$$

where $s_k, k \in 1, 2$ and $s_{3,i}$ are the signals of the cell-edge UTs and the cell-center UT in i^{th} cell, respectively. In NOMA system, BS assign power allocation coefficient to the users based on their channel gain such that lesser power is allocated to the user with higher channel gain, i.e., $\alpha_3 < \alpha_2 < \alpha_1$ with the SIC decoding order $U_1 \rightarrow U_2 \rightarrow U_{3,i}$. After subtracting the previous user's decoded signals, there is interference from $U_{3,i}$ at the U_2 and no interference at the $U_{3,i}$. Thus, the received signals at cell-center UTs, $U_{3,i}$, in i^{th} cell and k^{th} cell-edge UT are obtained as

$$y_{3,i} = \sqrt{\alpha_3 P_t} \hat{h}_{3,i} s_{3,i} + z_{3,i}, i \in \{1, 2\} \quad (3.57)$$

$$y_k = \sum_{i=1}^2 \left(\sqrt{\alpha_k P_t} \hat{h}_{k,i} s_k + \sum_{k'=k+1}^3 \sqrt{\alpha_{k'} P_t} \hat{h}_{k,i} s_{k',i} \right) + z_k, k \in \{1, 2\} \quad (3.58)$$

where $z_{k,i} \sim \mathcal{CN}(0, \sigma_n^2)$ is the AWGN. The received SINRs of decoding U_1 and U_2 at U_3 in each cell i and U_1 at U_2 are respectively given by

$$\gamma_{k \rightarrow 3,i} = \frac{\alpha_k \rho |\hat{h}_{3,i}|^2}{\sum_{k'=k+1}^3 \alpha_{k'} \rho |\hat{h}_{3,i}|^2 + 1}, i \in \{1, 2\}, k \in \{1, 2\}, \quad (3.59)$$

$$\gamma_{1 \rightarrow 2} = \frac{\sum_{i=1}^2 \alpha_1 \rho |\hat{h}_{2,i}|^2}{\sum_{i=1}^2 \sum_{k'=k+1}^3 \alpha_{k'} \rho |\hat{h}_{2,i}|^2 + 1}, \quad (3.60)$$

where $\rho = P_t/\sigma_n^2$ is the transmit SNR. Then, the SINRs of the UTs to decode their own signals after successfully performing SIC is expressed as

$$\gamma_{3,i} = \alpha_3 \rho |\hat{h}_{3,i}|^2, i \in \{1, 2\} \quad (3.61)$$

$$\gamma_k = \frac{\sum_{i=1}^2 \alpha_k \rho |\hat{h}_{k,i}|^2}{\sum_{k'=k+1}^3 \alpha_{k'} \rho |\hat{h}_{k,i}|^2 + 1}, k \in \{1, 2\}. \quad (3.62)$$

3.7.3. Channel statistics

In this section, the distributions of the channel gains of the UTs in the proposed network are determined first in order to discuss the derivation of the OP. The direct path channel amplitude of the U_1 and $U_{3,i}$ simply follow the Rayleigh distribution since the channel coefficients are assumed to be complex Gaussian RVs. Then, $X_{k',i} = |\hat{h}_{k',i}| \sim \text{Ray}(\sigma_{k',i} = \sqrt{d_{k',i}^{-\eta_a}/2}), k' \in \{1, 3\}$ with mean $\mathbb{E}[X_{k',i}] = \sigma_{k',i} \sqrt{\pi/2}$ and variance $\text{Var}[X_{k',i}] = \sigma_{k',i}^2(4 - \pi)/2$ [189]. Then, square of the Rayleigh RV becomes chi-square RV with $v = 2$ Degrees of Freedom (DoF), $X_{k',i}^2 \sim \mathcal{X}^2(v)$, which is a special case of Gamma distribution; Gamma $(\beta_{k',i}, \lambda_{k',i})$ with shape $\beta_{k',i} = v/2$ and scale $\lambda_{k',i} = 2\sigma_{k',i}^2$ [165], [189]. At the cell-edge UT, U_1 , the total channel gain is $|\hat{h}_{1,1}|^2 + |\hat{h}_{1,2}|^2$. Given that the Gamma RVs are independent, the distribution of the sum of them can be approximated as Gamma (β_1, λ_1) [172], where

$$\beta_1 = \frac{(\sum_{i=1}^2 \beta_{1,i} \lambda_{1,i})^2}{\sum_{i=1}^2 \beta_{1,i} \lambda_{1,i}^2}, \lambda_1 = \frac{\sum_{i=1}^2 \beta_{1,i} \lambda_{1,i}^2}{\sum_{i=1}^2 \beta_{1,i} \lambda_{1,i}}. \quad (3.63)$$

At U_2 , channel statistics are derived for two cases: exact channel gain and lower-bound channel gain. Considering both BS-RIS-UT path with the optimized phase-shift and the

direct path, the exact channel gain is given by

$$X_{2,i}^2 = |\hat{h}_{2,i}|^2 = \left(\sum_{m=1}^M |\bar{h}_{i_m}| |g_{i_m}| + |h_{2,i}| \right)^2 \quad (3.64)$$

$$= \left(\sum_{m=1}^M |\bar{h}_{i_m}| |g_{i_m}| \right)^2 + 2|h_{2,i}| \sum_{m=1}^M |\bar{h}_{i_m}| |g_{i_m}| + |h_{2,i}|^2. \quad (3.65)$$

In the first and second terms of (3.65), since $|\bar{h}_{i_m}| \sim \text{Ray} \left(\sigma_{h_i} = \sqrt{d_{r_i}^{-\eta_c}/2} \right)$ and $|g_{i_m}| \sim \text{Ray} \left(\sigma_{g_i} = \sqrt{d_{b_i}^{-\eta_b}/2} \right)$, their multiplication follows a double Rayleigh distribution [168]. In the case where $M \gg 1$ following Central Limit Theorem (CLT), the sum of M Independent and Identically Distributed (i.i.d) double Rayleigh RV, $Y_i = \sum_{m=1}^M |\bar{h}_{i_m}| |g_{i_m}|$, results in a Gaussian RV with mean $\mu_{Y_i} = \mathbb{E}[Y_i] = M \frac{\pi}{4} \sqrt{d_{r_i}^{-\eta_c} d_{b_i}^{-\eta_b}}$ and variance $\sigma_{Y_i}^2 = \text{Var}[Y_i] = \mathbb{E}[Y_i^2] - \mu_{Y_i}^2 = M(1 - \frac{\pi^2}{16}) d_{r_i}^{-\eta_c} d_{b_i}^{-\eta_b}$. In this case, it can also be approximated as a Gamma distribution with $\beta_{Y_i} = \mu_{Y_i}^2 / \sigma_{Y_i}^2$ and $\lambda_{Y_i} = \sigma_{Y_i}^2 / \mu_{Y_i}$ based on moment-matching method [168]. Consequently, the distribution of $X_{2,i}$; the sum of Gaussian and Rayleigh RVs, can be approximated by Gamma distribution; $X_{2,i} \sim \text{Gamma}(\beta_{2,i}, \lambda_{2,i})$.

In order to find the shape and scale of the Gamma distribution, mean and variance of $X_{2,i}^2$ in (3.65) are firstly calculated. The exact mean and variance of $X_{2,i}^2$ can be obtained by substituting the n^{th} moments of the Rayleigh RV $X = |h_{2,i}|$, $\mathbb{E}[X^n] = (2\sigma^2)^{n/2} \Gamma(\frac{n}{2} + 1)$ [189] and non-central moments of the Gaussian RV, Y_i , $\mathbb{E}[Y_i^2] = \mu_{Y_i} + \sigma_{Y_i}^2$, $\mathbb{E}[Y_i^3] = \mu_{Y_i}^3 + 3\mu_{Y_i}\sigma_{Y_i}^2$, and $\mathbb{E}[Y_i^4] = \mu_{Y_i}^4 + 6\mu_{Y_i}^2\sigma_{Y_i}^2 + 3\sigma_{Y_i}^4$ [172] in (3.66) and (3.67).

$$\mathbb{E}[X_{2,i}^2] = \mathbb{E}[Y_i^2] + 2\mathbb{E}[X]\mathbb{E}[Y_i] + \mathbb{E}[X^2], \quad (3.66)$$

$$\mathbb{E}[(X_{2,i}^2)^2] = \sum_{n=0}^4 \binom{4}{n} \mathbb{E}[Y_i^{4-n}] \mathbb{E}[X^n] \quad [172], \quad (3.67)$$

$$\text{Var}[X_{2,i}^2] = \mathbb{E}[(X_{2,i}^2)^2] - \mathbb{E}[X_{2,i}^2]^2. \quad (3.68)$$

Considering a practical case, where the received signals from direct and RIS paths are not coherent waves, the lower-bound of the effective channel gain can be expressed as [166]

$$X_{2,i}^2 \geq X_{2,i_L}^2 = \sum_{m=1}^M |\bar{h}_{i_m}|^2 |g_{i_m}|^2 + |h_{2,i}|^2. \quad (3.69)$$

The distribution of X_{2,i_L}^2 can be approximately formulated as $\text{Gamma}(\beta_L, \lambda_L)$. Let $Z =$

$|\bar{h}_{i_m}|^2 |g_{i_m}|^2$, the mean and variance of X_{2,i_L}^2 can be derived as

$$\begin{aligned} \mathbb{E} \left[\sum_{m=1}^M Z \right] &= \sum_{m=1}^M \mathbb{E} [|\bar{h}_{i_m}|^2] \mathbb{E} [|g_{i_m}|^2] \\ &= M 4 \sigma_{h_i}^2 \sigma_{g_i}^2 = M d_{r_i}^{-\eta_c} d_{b_i}^{-\eta_b}. \end{aligned} \quad (3.70)$$

$$\mathbb{E} [h_{2,i}^2] = 2 \sigma_{2_i}^2 = d_{2_i}^{-\eta_a}. \quad (3.71)$$

$$\begin{aligned} \text{Var} \left[\sum_{m=1}^M Z \right] &= \sum_{m=1}^M \text{Var}[Z] = M (\mathbb{E}[Z^2] - \mathbb{E}[Z]^2) \\ &= M (\mathbb{E} [|\bar{h}_{i_m}|^4] \mathbb{E} [|g_{i_m}|^4] - (d_{r_i}^{-\eta_c} d_{b_i}^{-\eta_b})^2), \\ &= M 3 d_{r_i}^{-2\eta_c} d_{b_i}^{-2\eta_b}. \end{aligned} \quad (3.72)$$

$$\text{Var} [h_{2,i}^2] = \mathbb{E} [h_{2,i}^4] - \mathbb{E} [h_{2,i}^2]^2 = d_{2_i}^{-2\eta_a}. \quad (3.73)$$

By summing the means (3.70) and (3.71) and the variances (3.72) and (3.73), respectively, the lower-bound channel gain's mean and variance are obtained as

$$\mathbb{E} [X_{2,i_L}^2] = M d_{r_i}^{-\eta_c} d_{b_i}^{-\eta_b} + d_{2_i}^{-\eta_a}. \quad (3.74)$$

$$\text{Var} [X_{2,i_L}^2] = M 3 d_{r_i}^{-2\eta_c} d_{b_i}^{-2\eta_b} + d_{2_i}^{-2\eta_a}. \quad (3.75)$$

Then, (β, λ) parameter is obtained from the moment-matching formula as previously discussed. Similar to the JT-CoMP cell-edge user, U_1 , the received channel gain is the sum of the effective channel from both cell, i.e., $X_{2,1}^2 + X_{2,2}^2$ or $X_{2,2_L}^2 + X_{2,1_L}^2$. Thus, the effective β and λ can be also calculated using (3.63).

3.7.4. Outage probability (OP) analysis

In this section, the outage probability of the users are formulated. Generally, the outage of the k^{th} UT occurs when its SINR is less than the SINR's threshold $\gamma'_k = 2^{R_k} - 1$, which can be expressed using probability function, $\mathbb{P}[\cdot]$ as $P_k = \mathbb{P}[\gamma_k \leq \gamma'_k]$. R_k is the target rate of k^{th} UT in Bits Per Channel Use (BPCU). Due to the SIC decoding principle, the outage probability of the cell-center UTs can be derived as

$$\begin{aligned} P_{3,i} &= \mathbb{P} [\gamma_{1 \rightarrow 3,i} > \gamma'_1, \gamma_{2 \rightarrow 3,i} > \gamma'_2, \gamma_3 \leq \gamma'_3] \\ &+ \mathbb{P} [\gamma_{1 \rightarrow 3,i} > \gamma'_1, \gamma_{2 \rightarrow 3,i} \leq \gamma'_2] + \mathbb{P} [\gamma_{1 \rightarrow 3,i} \leq \gamma'_1]. \end{aligned} \quad (3.76)$$

Similarly the outage probability of the cell-edge RIS UT, U_2 , and U_1 is given as

$$P_2 = \mathbb{P}[\gamma_{1 \rightarrow 2} > \gamma'_1, \gamma_2 \leq \gamma'_2] + \mathbb{P}[\gamma_{1 \rightarrow 2} \leq \gamma'_1], \quad (3.77)$$

$$P_1 = \mathbb{P}[\gamma_1 \leq \gamma'_1] \quad (3.78)$$

The analytical outage probability expression of $U_{3,i}$, U_2 , and U_1 is expressed as

$$P_u = \frac{\gamma\left(\beta_u, \frac{\Psi_u^*}{\lambda_u}\right)}{\Gamma(\beta_u)}, \quad u \in \{(3, i), 2, 1\} \quad (3.79)$$

where $\Psi_u^* = \max\{\Psi_{1 \rightarrow u}, \dots, \Psi_{u \rightarrow u}\}$, $\gamma(\beta, s)$ is a lower incomplete Gamma function with upper-limit s , and $\Gamma(\beta) = (\beta - 1)!$ is a Gamma function.

Proof: Please refer to **Appendix A.2**.

3.7.5. Simulation setup

Monte Carlo simulations were performed for 10^4 trials using the simulation parameters summarized in **Table 3.7**. The distance between the BS, RIS, and UTs in each cell are

Table 3.7: Simulation parameters in CoMP-NOMA with RIS.

Parameters	Value	Parameters	Value
$d_{1,1} = d_{2,1}$	0.8	$\eta_a, \eta_b = \eta_c$	3.5, 2.2 [166]
$d_{1,2} = d_{2,2}$	1	$\alpha_1, \alpha_2, \alpha_3$	0.5, 0.4, 0.1
$d_{3,i}, i \in \{1, 2\}$	0.3, 0.2	R_1, R_2, R_3	0.6, 1.6, 2 BPCU
$d_{r_i}, i \in \{1, 2\}$	0.5, 0.4	$d_{b_1} = d_{b_2}$	1

normalized, and the power allocation coefficients are assigned as in [167], which is also considered $K = 3$ UTs. where $K = 3$ UTs are also considered. The direct path distances from the BS to the cell-edgeUTs are the same. RIS in each cell are assumed to be placed near U_2 to avoid interference to the other UTs. A lesser number of RIS elements, $M = 3$, is employed to realise the outage probabilities in the low SNR region with normalized distances. The target rates of U_1 , U_2 , and $U_{3,i}$ are selected as $R_1 = 0.6$, $R_2 = 1.6$ $R_{3,1} = R_{3,2} = 2$, respectively [167]. Throughout the comparisons, the analytical OP curves of the users are plotted according to (3.79) with different β_u and λ_u based on the respective channel statistics.

CHAPTER 4

4. RESULTS AND DISCUSSION

4.1. Reduced-Rank Joint Estimation Of DoA With Mutual Coupling

In this section, the performance of the proposed method is investigated and compared with those of FBSS-based algorithms with known MC such as JIO-FBSS and Capon-FBSS, and MV based-auto-calibration without rank reduction, or FBSS-calibration [70], [115].

Simulations were initially run for the power spectra of the proposed approach at input signal-to-noise ratio (SNR) of 20 dB, and the results are compared with JIO-FBSS with no calibration and JIO-FBSS with known MC. The comparison for this case is given in **Figure 4.1**. It can be seen that the proposed method can estimate the true DoAs precisely with

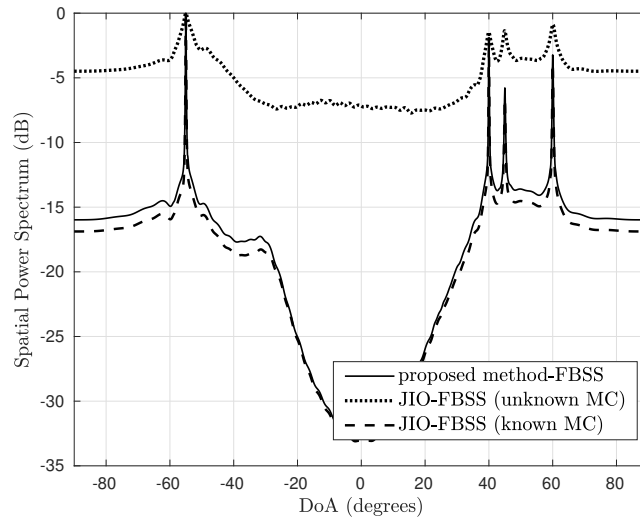


Figure 4.1: Comparison of spatial power spectra at SNR= 20 dB.

sharp peaks, similar to the JIO-FBSS with known MC. On the other hand, the spectrum peaks of JIO-FBSS with unknown MC are ambiguous even though FBSS helps to improve the DoA resolution. This shows that at high SNR, the performance of the proposed

method is as good as that of the JIO-FBSS algorithm with known coupling.

To get a better insight into the performance of the proposed approach, the comparisons in terms of RMSE of the DoA estimates are also performed and depicted in **Figure 4.2**. The RMSE is given as

$$RMSE = \sqrt{\frac{1}{N_s M} \sum_{s=1}^{N_s} \sum_{m=1}^M \left| \hat{\theta}_m(s) - \theta_m(s) \right|^2} \quad (4.1)$$

where N_s is the number of Monte Carlo simulations, and $\hat{\theta}_m(s)$ and $\theta_m(s)$ are estimated and true DoAs of m^{th} source at s^{th} simulation, respectively. Generally in all algorithms,

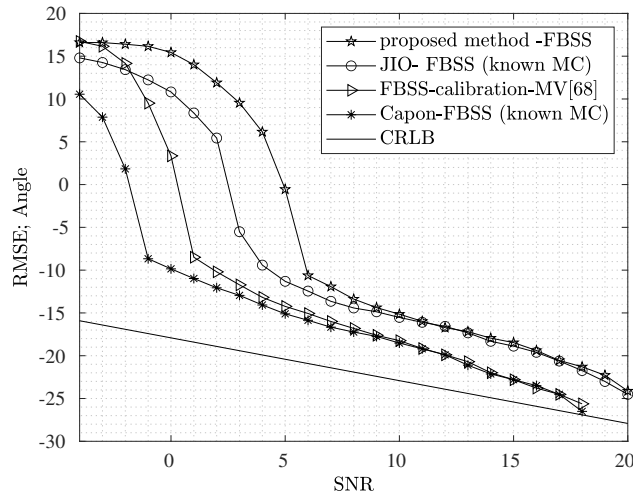


Figure 4.2: The RMSEs of DoA versus SNR at snapshot number= 20.

the low SNR values cause resolution problem in which the peaks of the power spectrum become ambiguous, leading to higher RMSE values, while at higher SNR values the RMSE curve linearly decrease with the SNR levels. Specifically, compared to the other methods, the RMSE values of the proposed method are larger at low SNR levels. As SNR increases the RMSE curve of the proposed method becomes the same as JIO-FBSS with known MC and approximately follows the trends of both Capon-FBSS with known MC and FBSS-calibration method. In addition to the RMSE curves of the existing methods, the Cramer-Rao Lower Bound (CRLB) for non-coherent signals with known MC is also shown as a comparison. From the RMSE analysis, it can be stated that the proposed method works well for practical SNR levels. At very low SNR levels, the performance is lower due to the sensitivity of coupling estimation using reduced rank covariance matrix which, on the other hand, causes the complexity of the proposed method to be much lower

than that of the others.

Next, the probability of successful estimation versus SNR is evaluated. Successful estimation is defined such that the average of the absolute estimation errors is within an estimation error threshold. The estimation error threshold is selected to be 2.5° , which is half a degree of the minimum DoA separation, so that when $|\hat{\theta}_m - \theta_m| < |\theta_m - \theta_{m+1}| / 2$, the adjacent DoAs θ_m and θ_{m+1} are successfully separable [115], [190]. As can be seen in **Figure 4.3**, the Capon-FBSS algorithm with known MC is superior to the other given approaches. However, it requires a higher computational cost when compared with the proposed method and JIO-FBSS. Moreover, both Capon-FBSS and JIO-FBSS algorithms

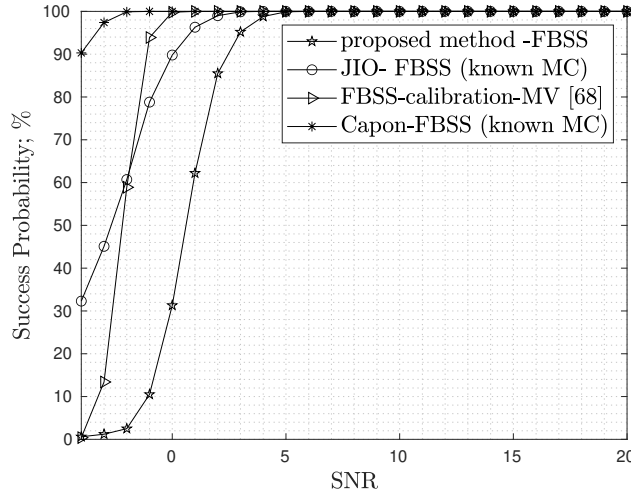


Figure 4.3: Probability of success versus SNR at snapshot number= 20.

hold the same curve pattern when SNR increases since MC is known in both of the methods. On the other hand, the curves of the proposed method and FBSS with MC calibration follow the same trend due to their MC calibration. At low SNR regions, the proposed method has about 3 dB lower performance than the FBSS-calibration on average. However, this can be taken as a trade-off between lower complexity and performance at lower SNR values. At high SNR values, the proposed method approaches a 100% success probability at 5 dB, followed by JIO-FBSS, FBSS-calibration and Capon-FBSS, with approximately 2 dB difference. The proposed method achieves the 100% probability later than the other approaches because of its mutual coupling calibration process.

In addition, the computational complexity of the proposed method is also compared and analyzed. Since FBSS-based algorithms are compared, zero cost is assumed for FBSS step. While the method of Wang et al. [70] has the complexity of

$O(N_t^3 + (\frac{180}{\Delta})N_t^2 + \alpha N_t^3)$, the proposed approach has

$$O\left(2\left[N_t^3 + \left(\frac{180}{\Delta}\right)r^3\right] + \left(\frac{180}{\Delta}\right)r^2 + \alpha r^3\right),$$

where α denotes the number of iterations that achieves the convergence threshold described in **Algorithm 3.2**. The complexity of the algorithm of Wang et al. [70] is due to the EVD of $\hat{\mathbf{R}}$ and $\mathbf{G}(\theta)$, and the grid search. As for the proposed method, $O(2[N_t^3 + (\frac{180}{\Delta})r^3])$ is due to the matrix inversion of the covariance matrix and the corresponding reduced-rank matrix in the rank-reduction process, which is repeated twice. The terms $O((\frac{180}{\Delta})r^2)$ and $O(\alpha r^3)$ are because of the grid search and EVD of reduced-rank $\mathbf{G}(\theta)$, respectively. For the simulation framework, since $r = 5$ and $N_t = 50$ were chosen, the reduced rank size is $r \ll N_t$, and thus the computational complexity of the proposed method is much lower than those of the conventional methods. For future 5G and beyond technologies, where large size of antenna arrays are deployed at BS, it is essential to implement low complexity based signal processing algorithms since the computational complexity of the existing conventional algorithms become higher with the large number of antenna elements. Therefore, the proposed method, which exhibits a satisfactory performance for coherent signals at realistic SNR and with a lower complexity compared to the existing techniques, can be considered as one of the promising signal processing techniques in the future wireless systems.

Finally, the computational complexity is analyzed in terms of the average CPU time in second (s). The simulations are performed for all the methods discussed previously by varying the antenna array size from $N_t = 50$ to $N_t = 200$, while fixing the number of snapshots at $K = 20$. This is because the effect of the antenna array size on the computational complexity is more dominant compared to that of the number of snapshots in these methods. SNR = 20 dB is assumed and the subarray size is fixed at $P = 10$ for the FBSS process. **Figure 4.4** shows the elapsed time of the DoA estimation for all methods, where the simulations are performed for 100 runs on a computer with Linux Mint OS. As shown in **Figure 4.4**, the proposed method initially has a similar CPU elapsed time as the FBSS-calibration method without rank reduction at $N_t = 50$ because of the resulting smaller size of the array from FBSS process. However, as N_t becomes higher, the CPU time of the FBSS-calibration method increases rapidly. On the other hand, the CPU time of the proposed method does not change much, and it is less than FBSS-calibration method due

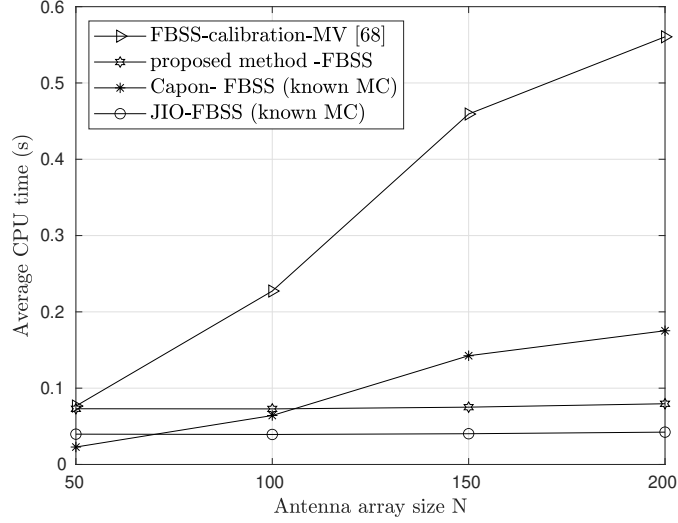


Figure 4.4: Average CPU time versus antenna array size, N_t at SNR=20 dB and K= 20.

to the fact that the reduced rank of the proposed method remains the same as the array size increases. Compared to the other methods with known MC, the proposed method has slightly larger CPU time because MC calibration process consumes some amount of time. Overall, the JIO rank reduction method with both known and unknown MC has an almost constant CPU consumption time as N_t increases due to its constant reduced rank.

4.2. Impact Of Mutual Coupling On Power-Domain Non-Orthogonal Multiple Access (NOMA)

In practice, electromagnetic interaction between the antenna array elements, known as mutual coupling, occurs in any array geometries and affects the steering vector. Consequently, the transmit antenna beam pattern is no longer directed towards the desired user direction. In the following subsections the practical array pattern due to mutual coupling and its effect on the achievable sum-rate of the NOMA system will be discussed. Afterward, a solution to this problem in the form of mutual coupling compensation will be presented. Three different radiation patterns are shown; *theoretical pattern* based on the pattern multiplication method that assumes no mutual coupling, *practical pattern* that includes the effect of mutual coupling, and *compensated pattern* that is the pattern after mutual coupling has been compensated for the array structure.

4.2.1. Antenna array beam pattern in the presence of MC

Considering the mutual coupling effect in the antenna array, the transmitted beam pattern, $E(\phi, \theta)$, in XY-plane has become

$$E(\phi, \theta = \pi/2) = (\mathbf{C}\mathbf{a}(\phi))^H \mathbf{v}(\phi_1). \quad (4.2)$$

In order to visualize the effect of mutual coupling, antenna patterns based on ULA, 2-D UCA and 3-D UCA are generated using MOM Electromagnetic (EM) simulation. Without considering the NOMA system, the effect of mutual coupling on the transmit beam pattern and its compensation have been discussed in [176]. Here the same antenna structures are adopted as [176], but with a larger number of antenna elements in ULA and 2D-UCA to realize a highly directional beam. **Figure 4.5** shows the normalized farfield pattern in YZ-plane (thus, $E(\phi = \pi/2, \theta)$) steered towards the nearest user at 68° , using ULA with $d = 0.5\lambda$. Here, $\mathbf{v}$ is an excitation voltage vector, generated based on non-uniform

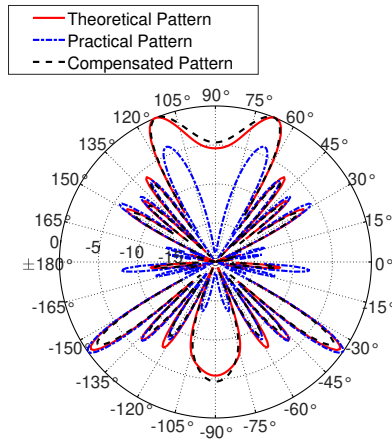


Figure 4.5: Normalized YZ-plane pattern with nearest UT-based beamformer, employing ULA with $N_t = 16$ and $d = 0.5\lambda$, MOM/EM simulation.

amplitudes and progressive phases to direct towards the desired user. It can be seen that the maximum gain of the practical pattern with MC is reduced by 4 dB approximately as compared to 0 dB gain of the theoretical pattern without MC. After mutual coupling is compensated as discussed in [176], the resultant pattern, shown by the dashed black lines, is approximately the same as the theoretical pattern. Therefore, the loss of 4 dB can be recovered by using this technique.

Similarly, mutual coupling significantly affects the far-field beam pattern in XY-plane (thus, $E(\phi, \theta = \pi/2)$) of UCA, as depicted in **Figure 4.6a**. Here, a UCA with $N_t = 8$ and

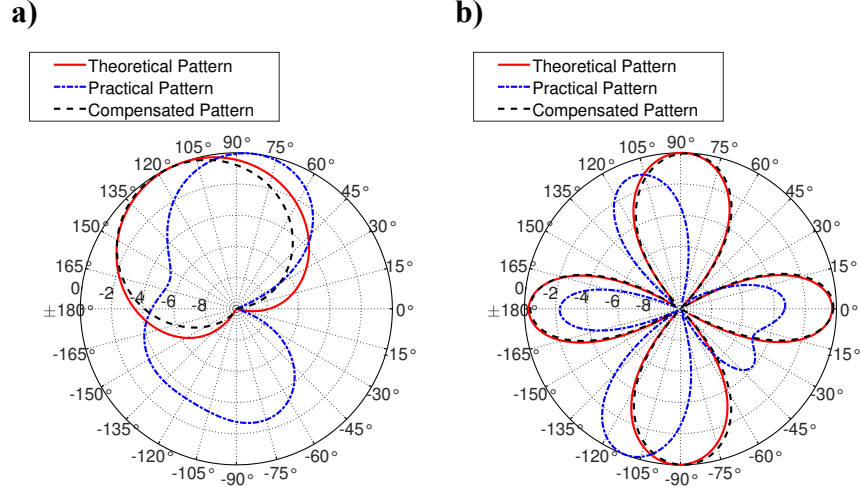


Figure 4.6: Normalized XY-plane pattern with nearest UT-based beamformer, employing: **a)** UCA with $N_t = 8$ and $r = 0.25\lambda$, **b)** staggered 3-D UCA in XY-plane, where the outer circle has $N_1 = 4$ with $r_1 = 0.5\lambda$, and the inner circle has $N_2 = 3$ with $r_2 = 0.4\lambda$ at $z = \lambda/4$, generated by MOM/EM simulation.

$r = 0.25\lambda$ is considered using uniform amplitudes and progressive phases beamforming. The theoretical beam, generated by nearest UT-beamforming, has the maximum gain at the desired direction $\phi_1 = 113^\circ$, while the practical beam is shifted towards $\phi_k = 84^\circ$, $k \neq 1$ due to MC. Again, it can be seen that the compensated pattern is in very good agreement with the theoretical pattern in the main beam direction. Finally, a 3-D UCA antenna array structure in XY-plane is considered, following the array configuration and the excitation voltages in [176], where the outer circle has $N_1 = 4$ with $r_1 = 0.5\lambda$, and the inner circle has $N_2 = 3$ with $r_2 = 0.4\lambda$ at $z = \lambda/4$. **Figure 4.6b** shows the far-field pattern for this array structure. We employ four main beams at $\phi_1 = -90^\circ$, $\phi_2 = 0^\circ$, $\phi_3 = 90^\circ$ and $\phi_4 = 180^\circ$ to target $G = 4$ groups of two-user NOMA system as a test case. The practical pattern shows a nearly 30° of beam shift from the desired direction of $\phi_1 = -90^\circ$ and $\phi_3 = 90^\circ$ due to MC accompanied by gain reduction. Similarly, for $\phi_2 = 0^\circ$ there is more than 3 dB loss with unwanted side-lobe, and $\phi_4 = 180^\circ$ has 2 dB loss in the main beam. Since such an antenna structure is widely used in BS, it can be observed that NOMA is nearly destroyed in this case. However, after compensating for the MC, it can be seen that not only the beam shift is steered back to the theoretical desired direction, but the gain reduction is also recovered.

In this section, the numerical results of Monte Carlo simulations are presented to evaluate the performance of the NOMA system in both DL and UL transmission links.

4.2.2. Uplink NOMA with ULA

Firstly, the simulations for UL NOMA are performed, where BS consists of ULA with size $N_t = 16$ and $d = 0.5\lambda$. The DoA of the UTs are $\phi = [68^\circ, 60^\circ, 52^\circ, 45^\circ]$, and all UTs send the signals to the BS simultaneously in the same frequency band. Here, it is assumed that the users utilize the maximum transmit power available to them as $p_k = P_t/4$, where P_t is the total transmit power of the users. Figs. **Figure 4.7a** and **Figure 4.7b** show the received power at the BS for each user after passing through the channel. It can be observed that the MATLAB simulation shows approximately the same results as EM simulation. In both scenarios with and without MC, the received powers at the far UTs are much lower than that of the nearest first UT since the far UTs have weak channel conditions. In the presence of MC, there is about a 4 dBm decrease in the received power of the nearest UT. **Figure 4.8** shows the total sum-rate of the system for both theoretical without MC

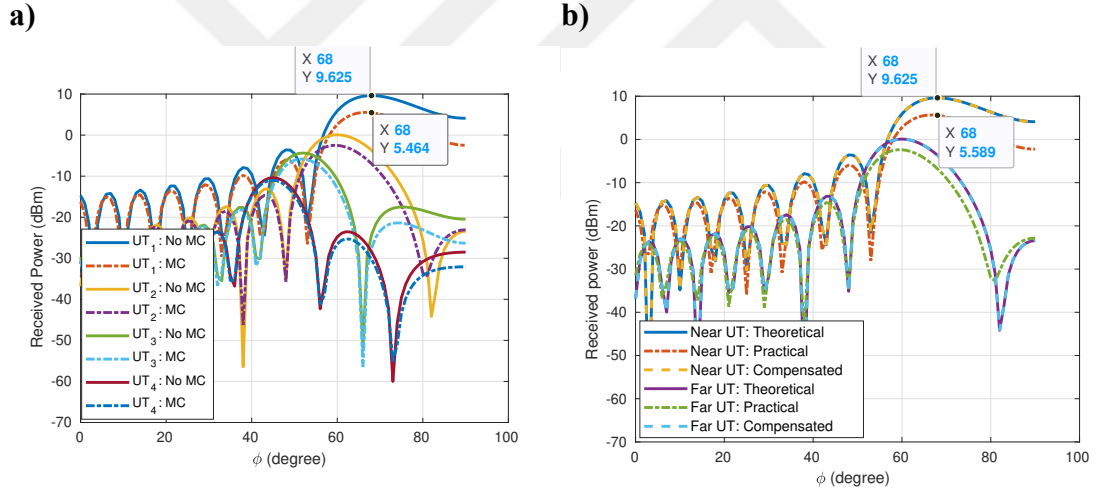


Figure 4.7: Received power for first and second UTs at the BS with the transmit power $p_k = 6.05$ dBm using **a)** EMF/MATLAB simulation, **b)** MOM/EM simulation.

effect and practical with MC effect using MATLAB and EM simulations. It can be seen that the sum-rate curve without mutual coupling compensation (MC) has about 1.5 bps/Hz degradation compared to the compensated or theoretical sum-rate in both MATLAB and EM simulations.

4.2.3. Downlink NOMA

In the following simulations for the DL NOMA, smaller power allocation coefficients are selected for the nearer UTs, based on their distances from the BS, as shown in **Table 3.1**.

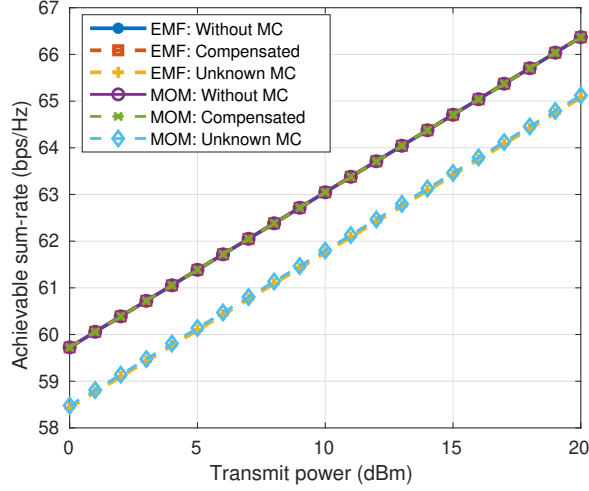


Figure 4.8: Total achievable sum-rate of UL NOMA using ULA with $N_t = 16$ and $d = 0.5\lambda$.

Three different configurations of array; ULA, UCA, and staggered 3-D UCA, are implemented at the BS.

4.2.3.1. Downlink NOMA with ULA

In the case of ULA with $d = 0.5\lambda$ in YZ-plane ($\phi = 90^\circ$), it is assumed that two users are located at $\theta = [68^\circ, 60^\circ]$ to demonstrate a basic NOMA system first. **Figure 4.9** displays the channel gain when MC affect is considered for ULA with $N_t = 16$ antenna, generated by EMF/MATLAB and MOM/EM simulations. In EMF/MATLAB simulation, where $\mathbf{v} = \mathbf{a}(\theta_1)$ is utilized, it can be seen that channel gain difference between the near UT at $\theta_1 = 68^\circ$ and the far UT at $\theta_2 = 60^\circ$ is around 10 dB, while in MOM/EM simulation, it is around 20 dB difference in the absence of MC. Additionally, in EM simulation with MOM, the reduce in channel gain due to mutual coupling is more significant because of its sharp drop pattern in the other directions, resulting from the non-uniform amplitudes and progress phases excitation voltages. Then, the total achievable sum-rate of DL NOMA system for both theoretical without MC, practical with unknown MC and with compensated MC are presented. It can be noticed from **Figure 4.10** that there is a difference of about 1 bps/Hz between the sum-rate curves with unknown MC for the EMF and the MOM simulations due to the different beamforming vectors. Thus, it can be summarized that the mutual coupling effect generated by MOM/EM simulation is worse than the EMF simulation with beamforming vector $\mathbf{v} = \mathbf{a}(\theta_1)$ due to the narrow beam generated by EM simulation using

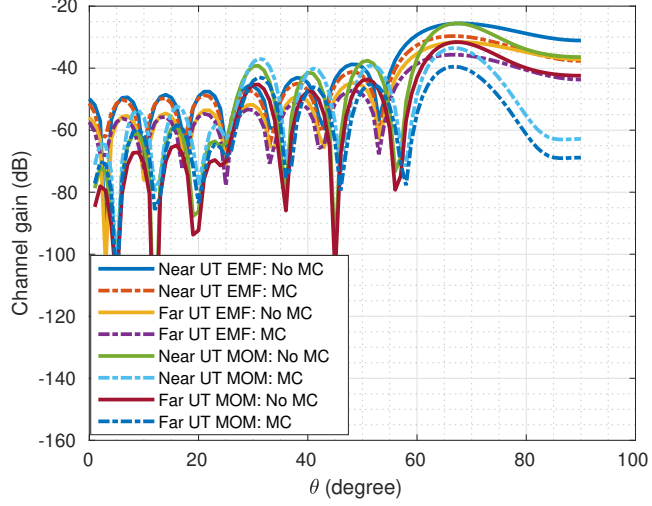


Figure 4.9: Channel gain resulting from nearest UT-based beamforming in ULA with $N_t = 16$, $d = 0.5\lambda$ and $\theta = [68^\circ, 60^\circ]$.

non-uniform amplitudes and progressive phases excitation voltages.

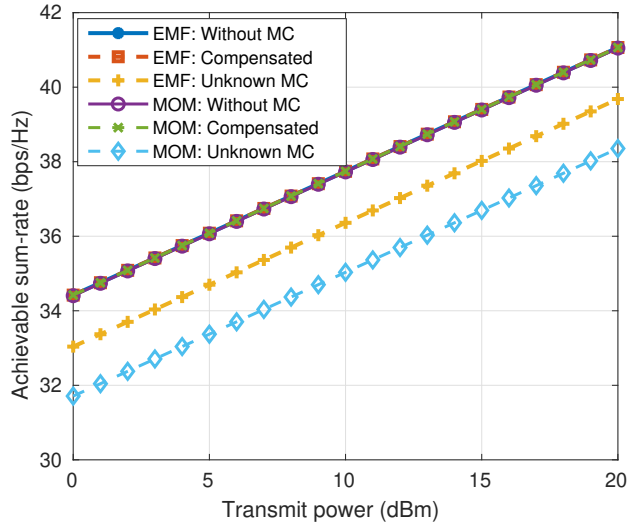


Figure 4.10: Total achievable sum-rate of DL NOMA using ULA with $N_t = 16$ and $d = 0.5\lambda$.

4.2.3.2. Downlink NOMA with UCA

In DL NOMA transmission where BS is equipped with one ring of UCA, it is considered that $K = 4$ UTs are served by a single beam. UCA with $N_t = 8$ and $r = 0.25\lambda$ in XY-plane ($\theta = 90^\circ$) is employed for 2-D UCA structure, and the main beam is steered to the direction of $\phi_1 = 68^\circ$, where the nearest UT is located. The other UTs are located at $\phi = [60^\circ, 50^\circ, 80^\circ]$, sequentially. **Figure 4.11a**, generated using by MOM/EM simulation,

illustrates the normalized transmit beam pattern based on the analog beamformer of the nearest UT, $\mathbf{v} = \mathbf{a}(\phi_1)$. Unlike the beam pattern of the UCA in **Figure 4.6a** where mutual coupling distorts the direction of theoretical beam, the beam pattern with MC in **Figure 4.11a** points the same direction as the theoretical, but with undesired back-lobe. Thus, it can be deduced that the effect of mutual coupling mainly depends on different beamforming techniques.

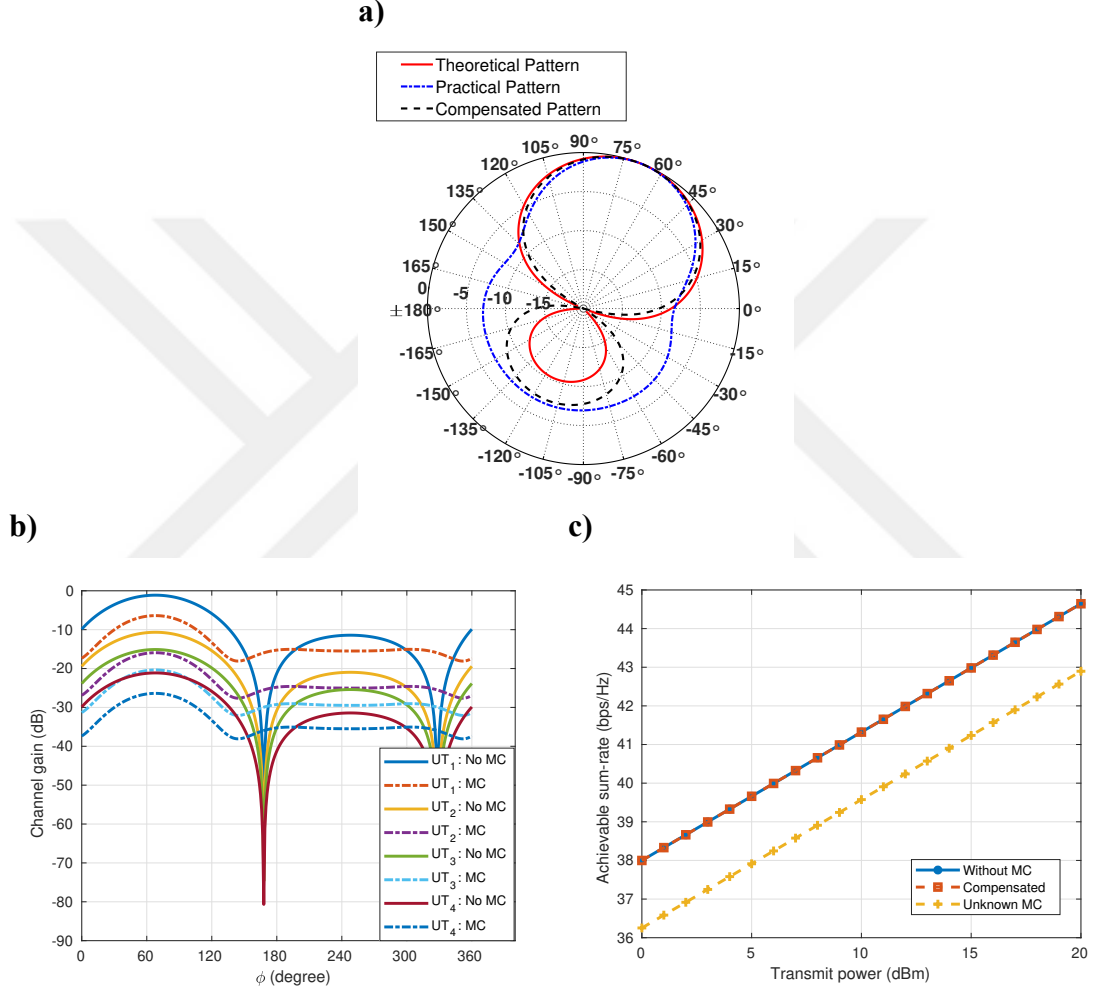


Figure 4.11: a) Normalized beam pattern, b) channel gain, c) total achievable sum-rate of DL NOMA with nearest UT-based analog beamformer $\mathbf{v} = \mathbf{a}(\phi_1)$ using UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [68^\circ, 60^\circ, 50^\circ, 80^\circ]$.

Using the same analog beamformer of the nearest UT, **Figure 4.11b** depicts the channel gains of $K = 4$ UTs in DL transmission. One may observe that in the presence of MC, there is approximately 5 dB drop in the channel gains of all UTs despite having the same directivity as the channel gains without MC. Based on the channel gain differences between the near and far UTs, SIC can be performed at the near UTs, following the scenario

in *Case 1*. The total achievable sum-rate is presented in **Figure 4.11c**, where there is a decrease of about 2 bps/Hz, caused by the loss in the channel gain due to MC.

Next, the sum-rate of the NOMA system is analyzed, where $K = 4$ UTs are sequentially located at different directions, $\phi = [113^\circ, 100^\circ, 90^\circ, 84^\circ]$. The effective channel gain curves based on the beam patterns generated by both MOM and EMF methods are shown in Figs. **Figure 4.12a** and **Figure 4.12b**. It can be seen in **Figure 4.12a** that with beam-

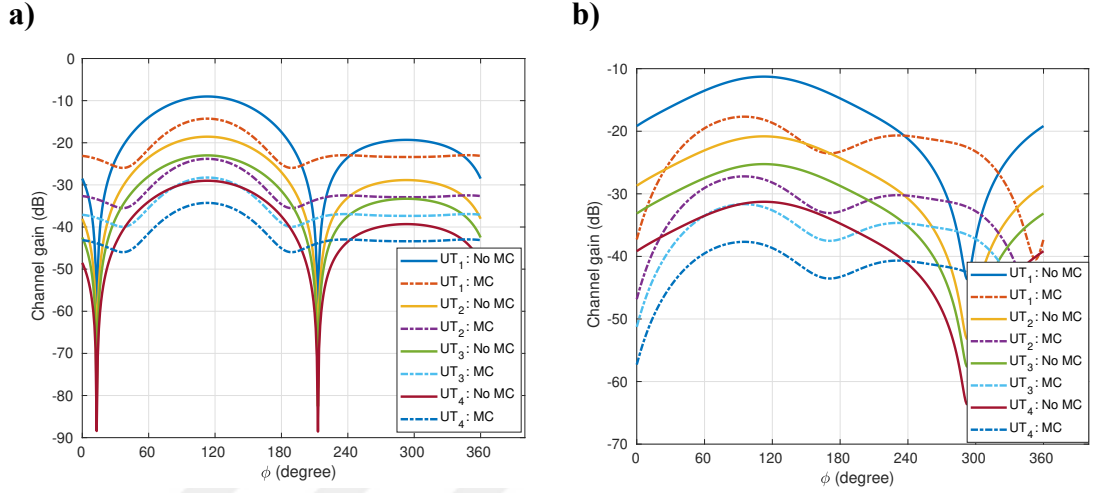


Figure 4.12: Channel gain resulting from near UT-based beamforming in UCA with $N_t = 8$, $d = 0.25\lambda$ and $\phi = [113^\circ, 100^\circ, 90^\circ, 84^\circ]$, generated by **a)** EMF/MATLAB simulation, **b)** MOM/EMF simulation.

forming vector $\mathbf{v} = \mathbf{a}(\phi_1)$ in EMF/MATLAB simulation there is a 6 dB drop due to mutual coupling. On the other hand, based on the beam pattern in **Figure 4.6a** generated by MOM/EM simulation when mutual coupling is considered, the peak of the effective channel gain curve is shifted to $\phi_4 = 84^\circ$ in addition to the gain drops for all the users, as shown in Figs. **Figure 4.12b**. Thus, without considering the channel path-loss, the near UTs have lower array gain than the far UTs, making the near UTs appear to be weaker users. This is the scenario mentioned above in *Case 2*. However, due to the path-loss difference, it can be seen that the effective channel gains with MC of the near UTs are still greater than that of the far UTs, resulting in the *Case 1* scenario.

The total achievable sum-rate of the system based on the *Case 1* scenario is plotted in **Figure 4.13**. It can be observed that due to the different beamforming techniques there is a difference of about 1 ~ 2 bps/Hz between the sum-rate curves generated by two methods in both the cases with and without MC. The sum-rate loss due to MC in MOM method is

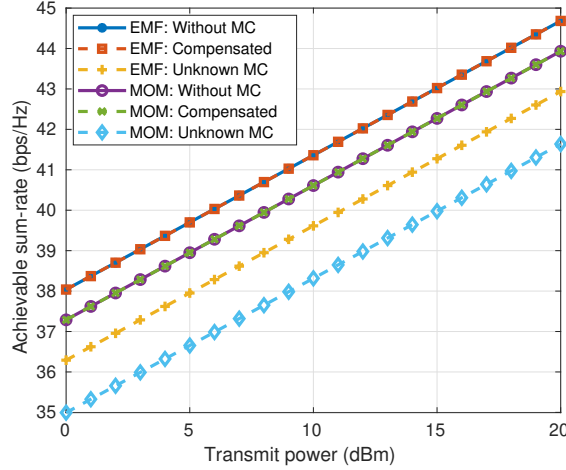


Figure 4.13: Total achievable sum-rate of DL NOMA using UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [113^\circ, 100^\circ, 90^\circ, 84^\circ]$ for the patterns generated by MOM and EMF methods.

more severe than that in EMF with $\mathbf{v} = \mathbf{a}(\phi_1)$ since the practical beam pattern generated by MOM/EM simulation is more distorted and steered away to the undesired direction.

4.2.3.3. Downlink NOMA with 3-D UCA

In 5G and beyond communication systems, such as Internet-of-Things (IoT) communication, vehicular-to-everything (V2X) communication and machine-type communications (MTC) that require stable and reliable connections across all directions with massive connections, NOMA with 3-D array structure can be exploited to support many users with full-directional beamforming [191], [192]. Therefore, next 3-D UCA is implemented, shown in **Figure 4.6b**, where the inner circle with $N_1 = 3$ and $r_1 = 0.4\lambda$ is located at $z = \lambda/4$ and the outer circle with $N_2 = 4$ and $r_2 = 0.5\lambda$ is placed at the origin in XY-plane. In this case, $G = 4$ number of 2-user groups are supported using 4 transmit beams generated by hybrid beamforming. $K = 8$ number of users are assumed to be located at $\phi_{g1} = [-90^\circ, 0^\circ, 90^\circ, 180^\circ]$ with $d_1 = 500$ m for near UT and at $\phi_{g2} = [-100^\circ, 10^\circ, 100^\circ, 170^\circ]$ with $d_2 = 1000$ m for far UT in respective group g .

Applying the combined weights of 4 analog beamforming vectors, $\mathbf{v} = \sum_{g=1}^4 \mathbf{v}_g$, at each antenna, the normalized beam pattern is illustrated in **Figure 4.14a**, generated by MOM/EM simulation. In order to see the effect channel condition in addition to the antenna array gain, the channel gain across different directions are then presented in **Figure 4.14b**, where the channel gains with MC are greatly reduced at all 3 directions except

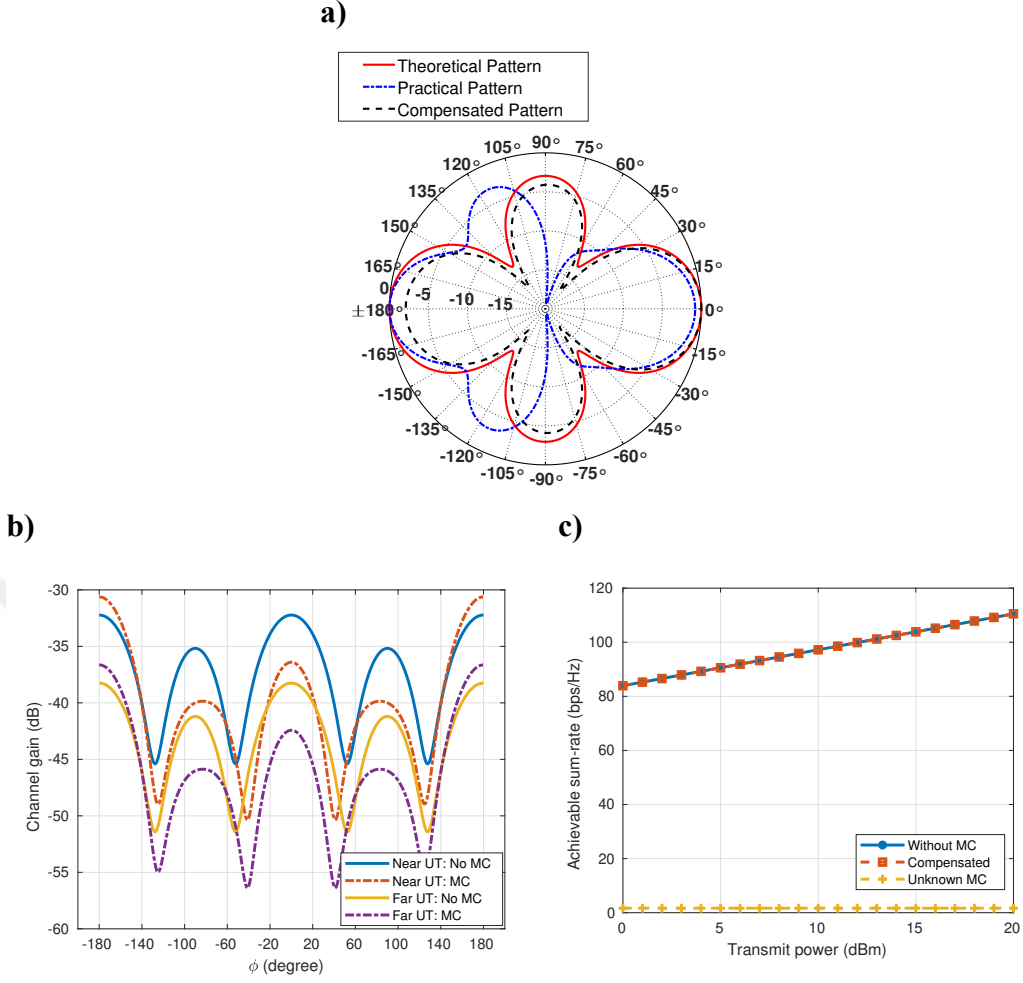


Figure 4.14: **a)** Normalized beam pattern, **b)** channel gain at all directions, **c)** total achievable sum-rate of DL NOMA with using combined near UT-based analog beamforming weights in 3-D UCA with $N_t = 8$, $r = 0.25\lambda$ and $\phi = [68^\circ, 60^\circ, 50^\circ, 80^\circ]$.

at the $\phi_4 = 180^\circ$ due to the broadside direction. Moreover, it can be observed that the channel gains with MC at the $\phi_1 = -90^\circ$ and $\phi_3 = 90^\circ$ are shifted by approximately 10° . Since there is a distinct channel gain difference between the near and far users, *Case 1* scenario is considered. It is worth pointing out that digital precoding is not applied here to calculate the channel gain, but rather only the combined analog beamforming weights are utilized, thus the interference caused by other groups cannot be observed in this simulation. Due to the mutual coupling, interference between the group cannot be perfectly canceled by ZF as seen in (3.29). The ZF-based hybrid beamforming in the presence of MCM causes very high inter-group and intra-group interference, which is eventually similar to the gain at the desired direction in each group. Additionally, inter-group interference

on the far user without MC is still high due to the ZF based on the near UT, while the inter-group interference on the near UT with no MC is much smaller than its channel gain. It can be seen in **Figure 4.14c** that due to the very high interference, the total achievable sum-rate of the system in the presence of MC does not benefit from the increase in transmit power and stays steady. Thus, it is essential to perfectly estimate the mutual coupling and compensate for it in order to keep the system sum-rate maximum.

4.3. Performance Analysis of User Scheduling in Massive MIMO with Fast Moving Users

In this section, Monte Carlo simulations are conducted to investigate user grouping and scheduling based on SUS algorithm and greedy algorithm in the fast moving users scenario. The initial simulations were performed for the user grouping and scheduling methods for both channel conditions with a different number of users, K , and signal-to-noise ratio, $\text{SNR} = 15$ dB. Rescheduling is performed at T_{frame} , assuming that the correct CSI at that time instance is predicted and known to the BS. As can be seen in **Figure 4.15**, the sum rate increases as the number of users increases for all the scheduling algorithms, and user scheduling provides a higher sum rate than grouping only without user scheduling. Compared to the greedy scheduling algorithm with statics users, both greedy rescheduling

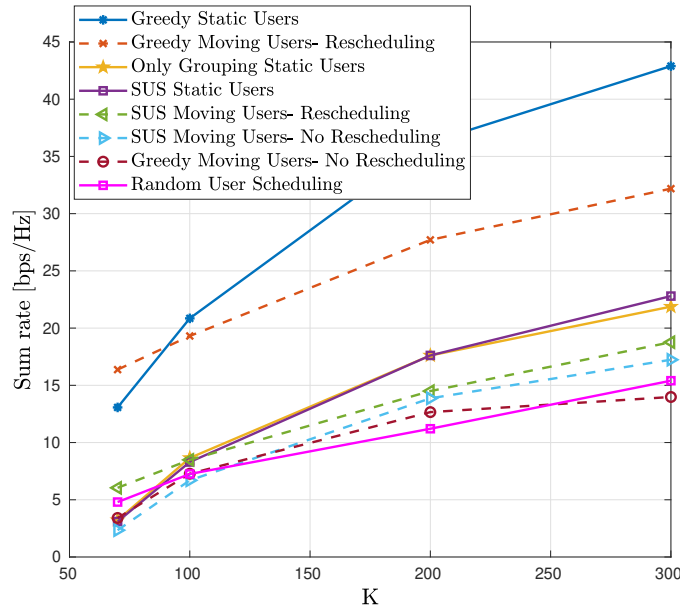


Figure 4.15: Sum-rate comparison of scheduling versus K at $\text{SNR} = 15$ dB and $T_{frame} = 6$ ms.

and outdated scheduled users in moving users have lower capacity due to the fast changing channel. Similarly, the same trend of the greedy algorithms can also be observed for the SUS algorithm in both moving and static users scenarios as K increases. Moreover, algorithms with rescheduling always outperform those with no rescheduling since rescheduling is performed according to the instantaneous channel characteristics related to the motion of the users.

Next, the simulations for the sum-rate comparison of the scheduling methods are performed with respect to SNR. The noise variance is fixed at 0 dB, thus SNR is the same as P_t . From **Figure 4.16**, it is observed that the performances of all the scenarios improve as SNR increases since more transmitted power are utilized. In the scenario of static users with grouping only, since all K users are simultaneously served without selecting S users, less power is allocated for each user, leading to lower average system capacity. It can be seen that without rescheduling, both algorithms are similar to random scheduling. It is also worth noting that greedy scheduling performs much better than SUS scheduling at the higher SNR levels since transmitted power is used in calculating system capacity during the process of selecting users in greedy algorithm, while SUS algorithm considers only norm of the channel gains.

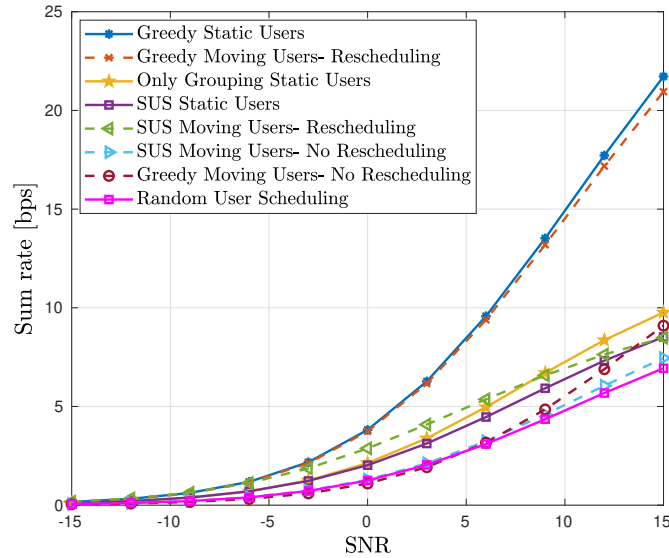


Figure 4.16: Sum-rate comparison of scheduling versus SNR at $K = 100$ and $T_{frame} = 6$ ms.

Finally, **Figure 4.17** represents a comparison of sum-rate for scheduling of both static users and moving users across different time frame lengths at $\text{SNR} = 15$ dB. The first scheduled

users are chosen by using the channel information predicted at initial $T_{frame} = 0$ s when the users are in a static state for both static and moving users environments. As it is assumed that the channels of the static users do not vary significantly in time, it can be seen that their system performance with both greedy and SUS algorithms do not change with time. At the next time frame from $T_{frame} = 6$ ms to $T_{frame} = 60$ ms, all K users in the moving scenario have already started moving and their channel condition changes with time. Thus, both scheduling techniques with no rescheduled users (outdated channel) based on the current channel state of the moving users have lower sum-rate compared to the scheduling methods with the rescheduled users. The performances of both greedy and SUS algorithm with the outdated channel are similar to that of random scheduling. With rescheduling by taking advantage of the correctly predicted channel at the next time instances, greedy algorithm performs much better than its outdated channel scheduling, while the capacity resulting from SUS rescheduling is more or less the same as its static user scheduling.

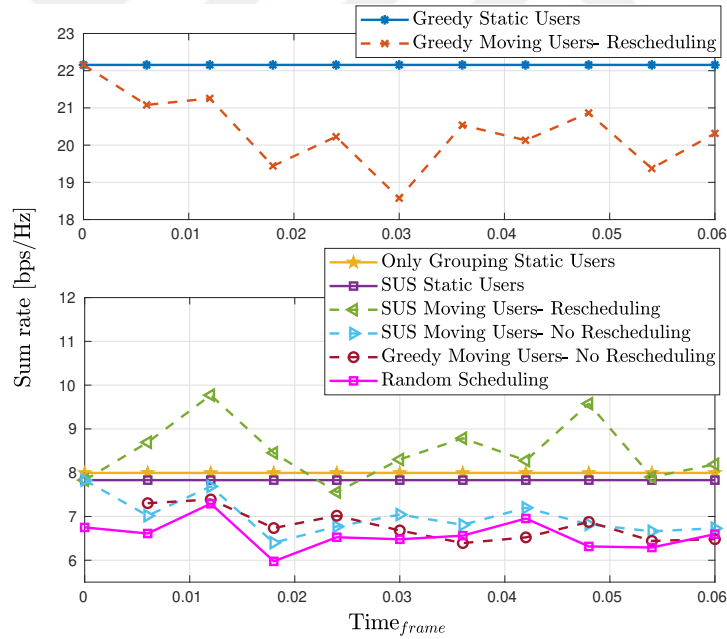


Figure 4.17: Sum-rate comparison of scheduling versus T_{frame} at SNR = 15 dB with $K = 100$.

4.4. Low-Complexity Deep Learning-Based Beamforming In MISO Systems

The complexity in terms of the number of Floating-Point Operations (FLOPs) for the proposed BFNN is discussed here, considering only the online implementation [193]. The

number of FLOPs for a CL is calculated as summation of multiplication and addition operations [194]. Assuming d_i number of input neurons, kernel size of z with stride 1, and F_i (F_o) number of input (output) kernels in each CL, there are $d_o = d_i - z + 1$ number of output neurons for each kernel. In this case, the number of FLOPs for the CL is calculated as a summation of the following operations for all number of kernels: $z \times d_o \times F_i \times F_o$ multiplication operations and $(z - 1) \times d_o \times F_i \times F_o$ addition operations in convolution processes, $d_o \times F_i \times F_o$ bias addition operations, and $(F_i - 1) \times d_o \times F_o$ addition operations across the convoluted input channels. Thus, the total number of FLOPs for the CL is obtained as $2z \times d_o \times F_i \times F_o$, while for FC layer, the total FLOPs is given as $2d_i \times d_o$ including the bias additions [144].

Following the hyper-parameters of the proposed network in **Table 3.3** with $N_t = 64$, the total number of FLOPs of the proposed CNN model is calculated as around 0.11 million. On the other hand, the number of FLOPs of the FCNN model in [144] is approximately 0.15 million. In comparison, SVD and matrix inversion operations utilized by the traditional HB approaches such as OMP [38] and PE-Alt [39], and SVD-based Fully-Digital (FD) [38] result in the complexity of $\mathcal{O}(N_t^3)$, that is about 0.26 million number of complex multiplications. Additionally, the number of parameters (params.) of the proposed network is around 30×10^3 , which is less than half of the BFNN in [144]. Due to lesser complexity, the speed of online execution increases and the allocated memory decreases, leading to a faster data transmission and lower hardware cost in real time scenarios. The complexity comparison is summarized in **Table 4.1**.

Table 4.1: Complexity comparison.

Method	Number of Params.	Number of FLOPs
Proposed CNN-BFNN	30, 836	0.11 million
FCNN-BFNN [144]	76,224	0.15 million
Traditional Methods	-	0.26 million

Next, the performance of the proposed CNN-BFNN model is evaluated in terms of system SE with respect to SNR values and is compared with the conventional beamforming techniques [38], [39] and the FCNN model, which uses the same hyper-parameters reported in [144].

Figure 4.18 depicts the SE performance comparison of the proposed CNN model, FCNN model [144] and the conventional methods such as OMP [38], FD [38] and PE-Alt [39].

The FD utilizes SVD-based digital beamforming technique, which provides higher SE than that of AB and HB. It can be seen that the proposed CNN model in each data representation results in a higher SE than the conventional methods and a lesser SE than FD. However, the proposed model, which uses FFT input and the ESOM arrangement,

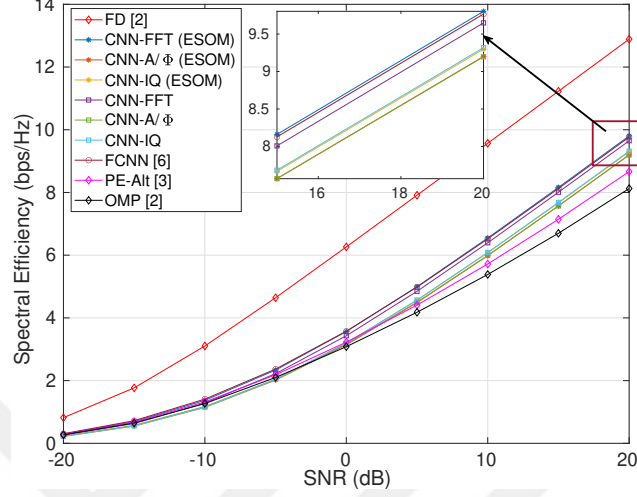


Figure 4.18: Spectral efficiency comparisons of conventional beamforming approaches and BFNNs with different data representations at PNR= 0 dB.

provides similar performance to FCNN. Among different data representations, CNN with complex-valued FFT provides the best performance compared to IQ and A/Φ formats, which agrees with the findings in [184]. At high SNR values, it is observed that the SE of the proposed model with respect to FFT input in the case of utilizing the ESOM arrangement is higher than that of the case without the ESOM arrangement. For other data representations, their respective SE performance is the same regardless of using ESOM.

Hence, it can be deduced that the ESOM arrangement lets the CNN exploit the local correlation between real and imaginary components of the frequency domain channel, allowing the CNN to learn more descriptive and discriminative features. The robustness of the proposed model against the channel estimation error (estimated number of path, L_{est}) is demonstrated in **Figure 4.19**. It can be seen that although the SE of the proposed CNN model is slightly lower than that of FCNN, it provides higher SE compared to the conventional beamforming schemes, where the difference is smaller for more accurate L_{est} .

With FCNN [144], the number of antennas can be increased to achieve better performance, at the cost of higher complexity. Contrarily, due to the nature of CNNs, the increase

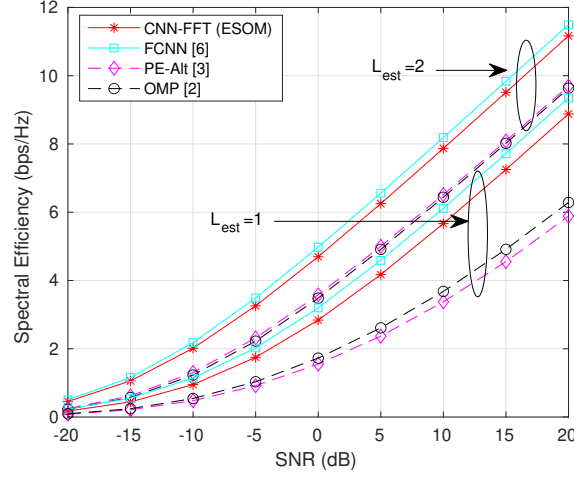


Figure 4.19: Spectral efficiency comparisons of conventional beamforming approaches and BFNNs for different L_{est} at PNR= 20 dB.

in antenna size increases the proposed network size with a reduced computational cost. Besides, it can be observed from the kernel size in each CL that a large kernel size is used in the first layer, followed by the smaller kernel size in the deeper layers. Adopting a larger kernel size in the first layer of CNN model considers full correlation among the channel coefficients. The reason is that a large kernel size allows the input channel coefficients across many antenna elements to be involved in generating each convoluted neuron to the next layer, leading to an efficient feature extraction for the next layer.

4.5. Joint Overlap Ratios and Power Allocation with User Fairness in Partial Non-Orthogonal Multiple Access (P-NOMA)

In this section, the performance of the proposed algorithm for the P-NOMA system is investigated and compared with the conventional NOMA and OFDMA systems.

Figure 4.20 shows the results of the simulation, performed at the distance ratio between the users, $d_r = 1 : 2$, for the sum-rate, user fairness, and power allocation coefficient, with respect to OR pairs. The contour graph of the total sum-rate is depicted in **Figure 4.20a**, which was obtained via exhaustive search by selecting the highest sum-rate of each (α, β) that satisfies the target fairness, in order to analyze the sum-rate across the OR pairs. It can be seen in **Figure 4.20a** that the maximum S is located at $(1, 0.7)$. At that ORs, the fairness reaches to 0.7, and $\gamma = 0.24$ as shown in **Figure 4.20b** and **Figure 4.20c**, respectively. It can also be observed in **Figure 4.20b** that the highest fairness is achieved at $(0, 1)$, where

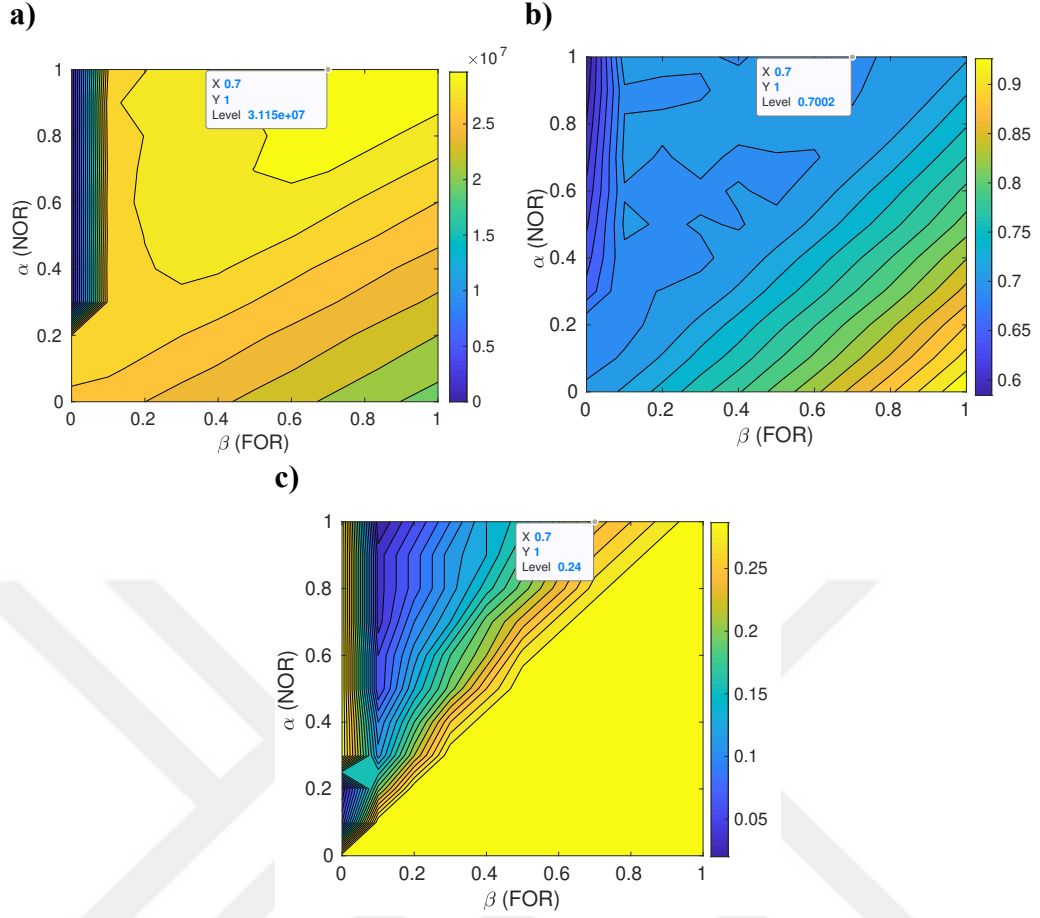


Figure 4.20: Contour graphs of **a)** Total sum rate, **b)** User fairness, **c)** Power allocation coefficient, with respect to ORs under $F_t = 0.7$, $d_r = 1 : 2$, $SNR_k = 10$ dB, using exhaustive search.

the far UT occupies all bandwidth of the near UT using NOMA, in addition to utilizing its own bandwidth using OMA. However, allocating more resources to the far UT to be absolutely fair can cause a decrease in the sum-rate of the near UT, eventually leading to a reduced total sum-rate, compared to the optimum sum-rate. Since the near UT is required to give up the β ratio of its bandwidth to the far UT, more power is allocated to the near UT to compensate for its sum-rate loss if the near UT does not utilize approximately the same ratio as β from the far UT's bandwidth, as can be observed in **Figure 4.20c**.

Next, simulations are performed for sum-rate and the respective user fairness using the proposed gradient search method in **Algorithm 3.3**, based on the distance ratio between the UTs. Here, the simulation environment is the same as the above simulation. The comparisons of the total sum-rate and the user fairness, among the optimum P-NOMA, NOMA and OMA, are shown in **Figure 4.21a** and **Figure 4.21b**, respectively. It can be seen that both sum-rate and user fairness values have a tendency to decrease as the distance

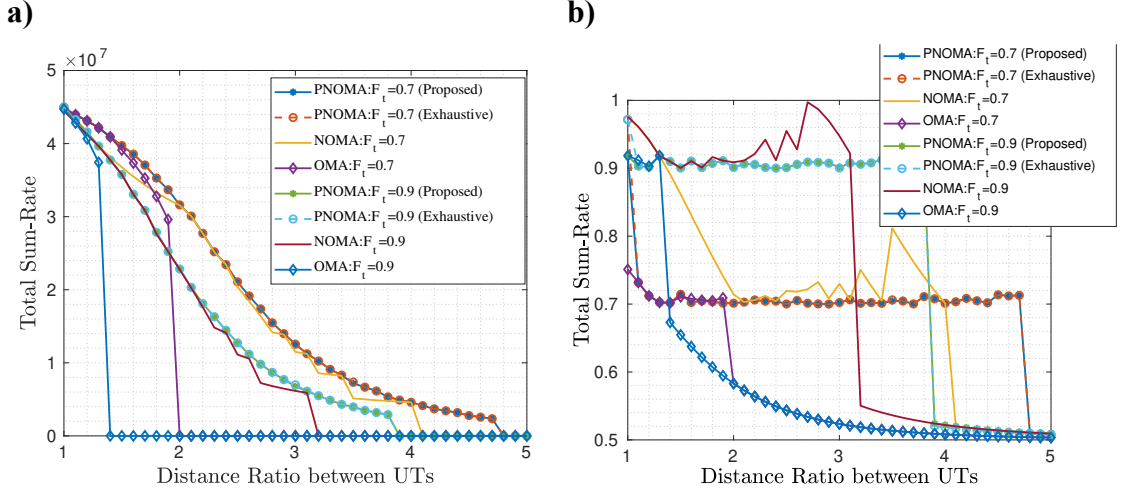


Figure 4.21: Comparison of **a)** Total sum rate, **b)** Jain's user fairness, based on distance ratio.

ratio increases due to the fact that channel gain of the far UT is decreased, leading to the decrease in its sum-rate as well as the fairness. It can be observed from both figures that the P-NOMA satisfies the desired user fairness around $F = 0.7$ while its sum-rate values are always higher than that of NOMA and OMA, except at the distance ratio, where the user fairness of the P-NOMA and the NOMA are closely the same. As for the OMA system, the sum-rate values, where $F_{OMA} < F_t$, are all zero. It can be deduced from these results that P-NOMA with the optimum ORs and the power allocation coefficient can provide a higher sum-rate while satisfying user fairness compared to other Multiple Access (MA) systems. Thus, for 5G and beyonds systems, instead of NOMA, P-NOMA can be a more preferable option.

4.6. Partial-Beam Non-Orthogonal Multiple Access (PB-NOMA) With Fuzzy Clustering

Numerical results for the proposed PB-NOMA are presented in this section. The membership values of the selected users in group 1 and 2, $\mathbf{F}^{(1)}$ and $\mathbf{F}^{(2)}$, are obtained, respectively.

$$\mathbf{F}^{(1)} = \begin{pmatrix} 0.5081 & 0.7272 \\ 0.4919 & 0.2728 \end{pmatrix}, \text{ and } \mathbf{F}^{(2)} = \begin{pmatrix} 0.4940 & 0.2748 \\ 0.5060 & 0.7252 \end{pmatrix}.$$

It can be seen that the membership values of the row $g = 1$ for all the columns $k_g \in \{1, 2\}$ in the first group, i.e. $\mathbf{F}_{1,k_g}^{(1)} = [0.5081, 0.7272]$, are higher compared to the values in the second row. That means this membership matrix is obtained correctly for the group

1. Similarly, in $\mathbf{F}^{(2)}$, the values in the second row are higher than those of the first row. Based on the user pairing algorithm, the required boundaries are also satisfied, e.g. $\mathbf{F}_{2,1}^{(1)} = 0.4940 \geq 0.4$ and $0.2 \leq \mathbf{F}_{2,2}^{(1)} = 0.2748 \leq 0.4$, that makes $\mathbf{F}_{g,k_g}^{(g)}$ belongs to the near UT in group $g, \forall g \in \{1, 2\}$. It is made sure that the membership value of the far UT is high enough to have a close relation with the near UT in the same group to avoid inter-group interference.

Figure 4.22 illustrates the contour graphs of the total sum-rate for each group g and for the whole system with constant ORs $\alpha_g = \beta_g = 0.7$. In group 1, the near UT occupies

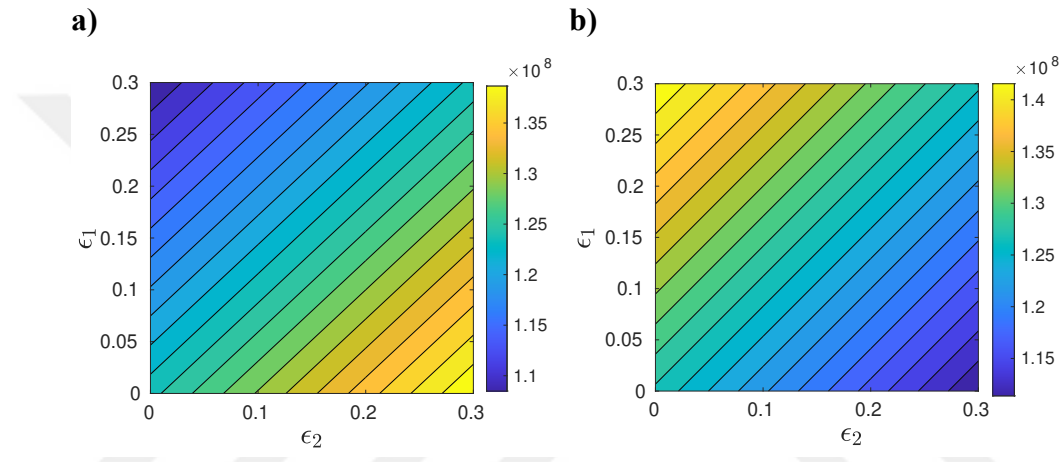


Figure 4.22: Contour graphs of total sum-rate for the PB-NOMA signal model with $\alpha_g = \beta_g = 0.7$ in **a)** group $g = 1$, and **b)** group $g = 2$, with respect to OBRs at $P_m = 10$ dB and $\sigma_m^2 = -2$ dB.

additional bandwidth from the near UT of group 2, which results in the maximum sum-rate when $\epsilon_2 = 1 - \beta_2$ value is the highest; 0.3 in this case. This happens only when $\epsilon_1 = 0$ since allowing the near UT of group 2 to utilize the bandwidth of group 1 can cause interference. Similarly, group 2 has the highest sum-rate at $(\epsilon_1, \epsilon_2) = (0.3, 0)$. Thus, higher sum-rate can be obtained in a preferable group by selecting a proper ϵ_g pair.

Next, the effect of $(\alpha_g, \epsilon_{g'}) \forall g \in \{1, 2\}$ on the sum-rates of near and far UTs is investigated in **Figure 4.23** since $(\alpha_g, \epsilon_{g'})$ are ORs of the near UT in group g . The pair of (α_1, ϵ_2) is first varied by fixing $(\alpha_2 = 0.7, \epsilon_1 = 0)$, letting $u_{1,n}$ use more bandwidth of the group 2. As can be seen in (a), overlapping in the same group using α_1 region tends to reduce the sum-rate of the $u_{1,f}$ due to the fact that α_1 region is sacrificed by $u_{1,f}$. On the other hand, decreasing α_1 and increasing ϵ_2 allocation to the overlapped beam region of the other group results in a slight increase for the sum-rate of $u_{1,f}$ and much higher sum-rate gain of $u_{1,n}$. However,

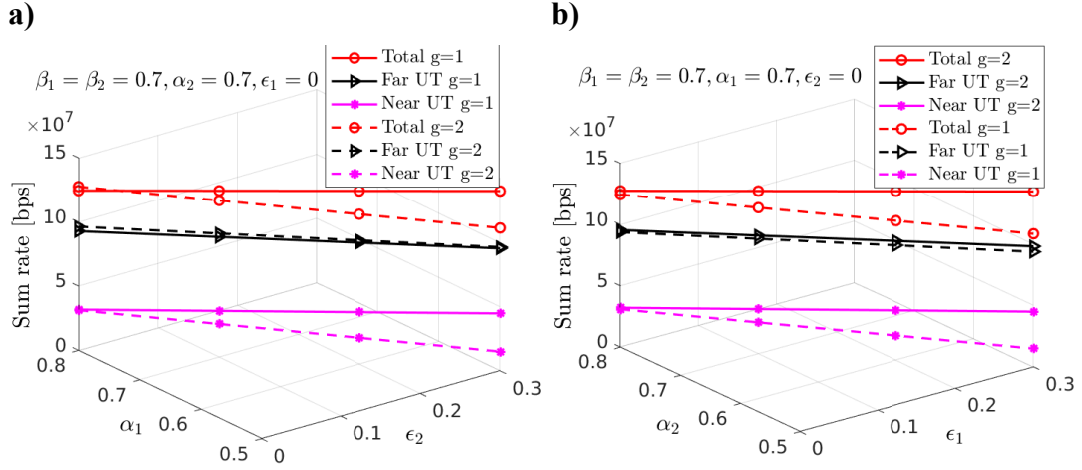


Figure 4.23: The effect of $(\alpha_g, \epsilon_{g'})$ on the sum-rates of the UTs in each group with $\beta_1 = \beta_2 = 0.7$ **a)** At $\alpha_2 = 0.7$ and $\epsilon_1 = 0$, **b)** At $\alpha_1 = 0.7$ and $\epsilon_2 = 0$.

there is a decrease in sum-rate of the near UT in group 2, $u_{2,n}$, due to the sacrificing of the bandwidth to the $u_{1,n}$. This shows that (3.52) is satisfied. Following the same trend of (α_1, ϵ_2) , the overall summation of the sum-rate in group 1 is increased. Similarly, the effect of (α_2, ϵ_1) on the sum-rate in the group 2 can be observed in **Figure 4.23b**. The same behavior as in the group 1 is found, i.e., there are higher sum-rates of the UTs in group 2 and a lesser sum-rate of $u_{1,n}$. It is worth noticing that the sum-rates of the near UTs are lesser than that of the far UTs due to the higher inter-group interference of the near UTs which is caused by the channel similarity in the overlapped cluster.

Figure 4.24 shows the comparison between PB-NOMA and P-NOMA. In the P-NOMA system, ϵ_g is fixed at 0 across all α_g values. As can be seen in **Figure 4.24a** and **Figure 4.24b**, in P-NOMA, the sum-rates of the far UTs in both groups increases as α_g values decrease, while that of the near UTs is reduced. On the other hand, in PB-NOMA, the reduced sum-rates of the near UTs are compensated by utilizing more bandwidth of the other group g' . Consequently, both near and far UTs achieve higher sum-rates by reducing α_g and increasing ϵ_g .

Thus, it can be deduced from these results that allocating more bandwidth in the overlapped beam region is preferable over utilizing the region in the same beam or group, considering the case that there are near users which are closely correlated. This observation is useful for the scenarios, where Quality of Service (QoS) for the far user is more important than the near user in a desired group.

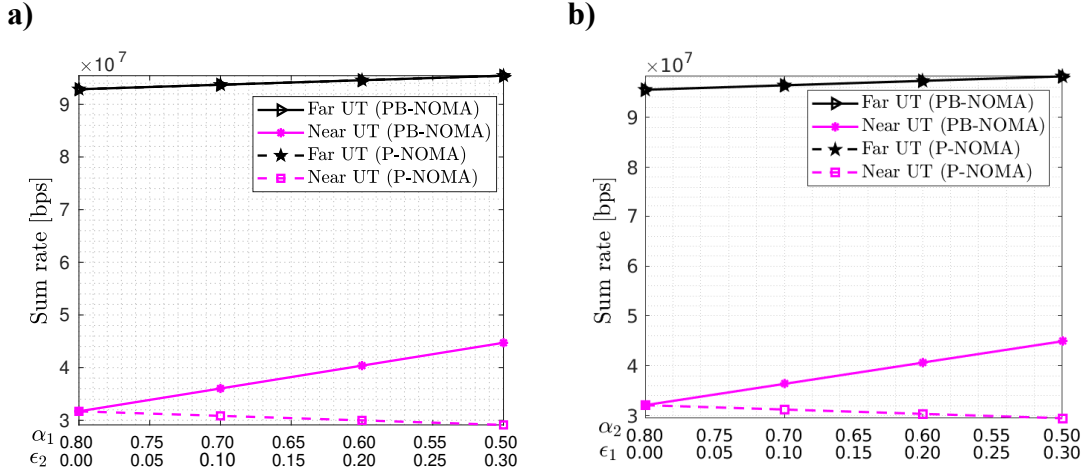


Figure 4.24: Sum-rate comparison between PB-NOMA and P-NOMA at $\beta_1 = \beta_2 = 0.7$ for a) Group 1 with $\epsilon_1 = 0$, b) Group 2 with $\epsilon_2 = 0$.

4.7. Outage Probability Analysis Of Reconfigurable Intelligent Surface-Enabled Coordinated Multi-points NOMA Networks

In this section, numerical results are discussed to validate the performance of the proposed system named as *RIS+Direct* and it is compared with the traditional JT-CoMP-NOMA without RIS; *Direct*, and JT-CoMP-NOMA with only RIS path without direct path; *RIS*.

In **Figure 4.25**, the outage probability of the cell-center UTs in each cell, and the cell-edge JT-CoMP-UTs are plotted against SNR. The traditional JT-CoMP-NOMA case, where there is no RIS in the system, is first considered. The simulated OP curves highly match with the analytical results of all UTs. Compared to the cell-edge UTs, the OP of the cell-center UTs is plotted individually for each cell. It can be observed that their outage performances at the higher SINR values are lower than that of the cell-edge UTs even though they have no interference in the received SINR after performing SIC. This is due to the fact that the cell-center UTs do not employ JT-CoMP scheme, resulting in received power from a single BS only. On the other hand, it can be seen that OP of U_2 is greater than that of U_1 since they both have similar channel gains due to the same distance, yet more power is allocated to U_1 , considering U_1 as the weaker user. Therefore, this assumption makes the outage performance of the U_2 worse than U_1 .

In the case of the proposed system with RIS-assisted transmission for U_2 , as shown in **Figure 4.26**, the OP performance of U_2 is significantly improved compared to the *Direct* case. The exact analytical OP curve for *RIS+Direct* system is plotted by (3.79) based

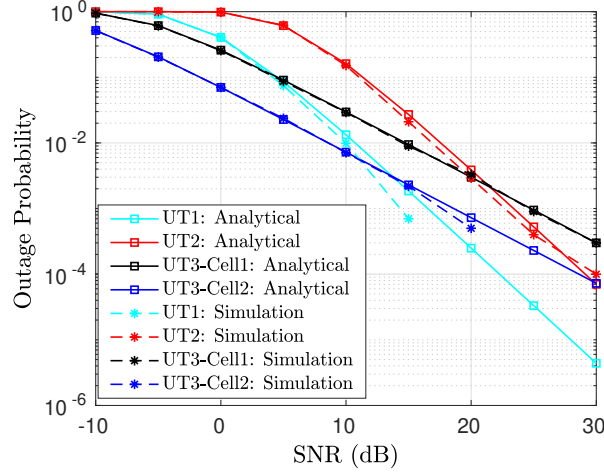


Figure 4.25: Outage probability of all UTs in traditional JT-CoMP-NOMA system without RIS; *Direct* case vs SNR.

on (3.66) and (3.68). The upper bound OP curve, which is the worse-case OP of the proposed system with *RIS+Direct* channel, is plotted based on the lower-bound channel gain statistics in (3.74) and (3.75). Even in the worst-case scenario of the proposed system, the OP of U_2 outperforms the traditional case with a direct path. It is also worth observing that the slope of the OP in the *RIS+Direct* case is the highest among the other cases. Thus, it can be deduced that the diversity order, which demonstrates how quick the OP reduces with the transmit SNR, is enhanced in the proposed system.

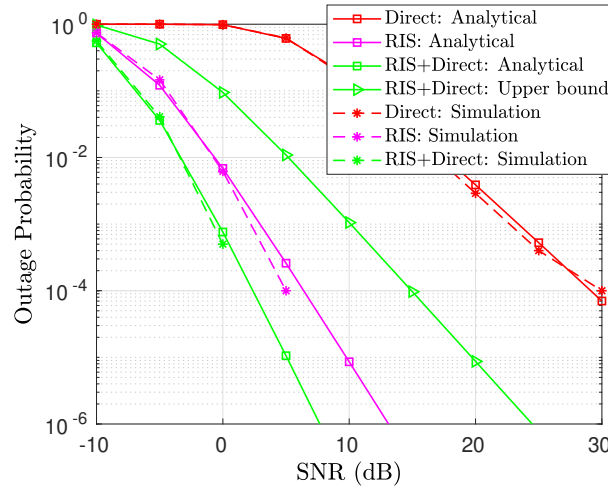


Figure 4.26: Outage probability of U_2 in different cases vs SNR.

CHAPTER 5

5. CONCLUSION AND FUTURE WORK

5.1. Conclusions

In this thesis, three essential technologies in 5G and beyond wireless networks and their challenges concerning complexity and spectral efficiency are presented by focusing on: 1) Low complexity issue in DoA and effect of MC, 2) Effect of user scheduling and low complexity beamforming design for massive MIMO, and 3) Utilization of NOMA with recent emerging technologies such as RIS and CoMP to improve the spectral efficiency and reduce interference. The summary of contributions and findings of each are recapped as follows:

In **Section 3.1**, a reduced-rank DoA estimation algorithm in the presence of MC for coherent signals was proposed. In order to decorrelate the incoming coherent signals, FBSS method is integrated into the JIO rank-reduction process. The JIO algorithm generates the reduced covariance matrix that is then used in Capon's power spectrum to estimate the DoAs. Next, MV-based auto-calibration method is performed to iteratively update the MC coefficients and the DoAs, followed by DoAs estimation in JIO-FBSS algorithm with the newly estimated MC coefficients. Simulation results show that the proposed algorithm not only provides accurate estimation of DoAs but also has lower computational complexity, which is suitable for massive MIMO systems in 5G and beyond networks. Due to its lower computational cost, the proposed algorithm is preferable for the DoA estimation with unknown mutual coupling when there is a small number of snapshots available with large array size and many sources.

Section 3.1 analyzed the effect of mutual coupling on the achievable sum-rate of the NOMA network. Since mutual coupling causes distorted antenna pattern at both UL and

DL transmission, the sum-rate of NOMA system with different antennas configurations at the BS such as ULA, 2-D UCA, and staggered 3-D UCA were analysed. Simulation results concluded that without proper compensation of mutual coupling, the far user receives higher channel gain from the distorted beam, resulting in incorrect SIC decoding and received SINR degradation. Especially in UCA, mutual impedance values are larger because of the symmetric antenna placement in a circular form. Hence, the sum-rate decrease is more significant in UCA, especially in the case with progressive phases beamforming in MOM/EM simulation owing to its shifted antenna pattern that results in a considerable drop in the desired channel gain. With the help of MC compensation, the effect of MC can be reduced, and thus compensation is encouraged to be applied in future applications of multi-antenna systems.

In **Section 3.3**, user grouping and scheduling in a massive MIMO system with FDD was analysed in the presence of fast moving users. Since signals are simultaneously transmitted to a group of users, the inter-group interference is mitigated by pre-beamforming based on Eigen beamforming, and the intra-group interference is cancelled by digital beamforming. Improved K-mean clustering with WLD similarity was used for grouping and two scheduling methods: SUS and greedy algorithms, were analyzed and compared. It was observed from the simulation results that rescheduling with a greedy algorithm enables the sum-rate performance of the moving users fluctuates around that of the static user, while the sum-rate of the greedy scheduling drops notably without rescheduling. On the other hand, rescheduling with SUS approach does not have any significant improvement. Therefore, when resources for rescheduling such as instantaneous channel information are not available, it is preferable to employ SUS algorithm with no rescheduling since it is less complex and has similar sum-rate performance as greedy algorithm with no rescheduling.

Section 3.4 discussed a low-complexity deep learning-based analog beamforming design in a massive MISO system. The proposed beamforming design is based on unsupervised learning that maximizes the system SE by training CNN model with a new input feeding arrangement called ESOM. Since the input of the network is a complex-valued channel vector, different types of input data representations such as FFT, A/ Φ , and IQ were utilized to decompose it into a real-valued vector. Compared to the traditional beamforming design and FC-BFNN, the proposed CNN-BFNN has significantly reduced complexity with a similar SE performance as FC-BFNN. Moreover, it was observed from the comparisons

of different input data representation that FFT representation outperforms both A/ Φ and IQ, which is in-line with the findings in the literature. Thanks to the low computational complexity, the proposed network is a suitable beamforming design in real-time signal processing, which plays an important role in fast data transmission required for 5G.

In **Section 3.5**, a joint power and ORs allocation algorithm in a P-NOMA system has been proposed. This algorithm is based on gradient search by maximizing the system sum-rate while satisfying the target user fairness. Compared to the exhaustive search, the proposed gradient search algorithm has lesser computational complexity by providing the same sum-rate performance. It is expected that P-NOMA integrated with beamforming, will be a promising MA technology that can achieve an improved spectral efficiency performance and minimize the interference caused by the conventional NOMA.

In **Section 3.6**, an extended version of P-NOMA in mmWave channel has been investigated. In the proposed system, since users are closely distributed, fuzzy clustering was implemented to group some users that belong to two groups. Simulation results demonstrated that in the proposed PB-NOMA, OBRs can be increased instead of the NOR in order to improve the sum-rate performance of the far user without affecting the sum-rate of the near user in the same beam. Therefore, the proposed system is capable of improving sum-rate performance in the presence of closely distributed users. Moreover, the proposed scheme can be applied in scenarios, where BS serves more far users with higher demand, and when re-transmission is needed for those users in case of poor channel conditions.

In **Section 3.7**, the outage probability of CoMP-NOMA networks with RIS was investigated. The proposed network includes a cell-center UT in each cell and two cell-edge UTs that are located at the same distance from the BSs. Closed-form expressions of the outage probability for all users were derived and compared with simulation results. The numerical results demonstrated that the use of RISs increases the channel gain of the cell-edge user 2 and hence its outage probability improves compared to the traditional CoMP-NOMA case. In addition, the diversity order of the proposed system is the highest. The proposed network is also applicable in the multi-cell NOMA networks with multiple users. In addition, the proposed system can be used to improve the system spectral efficiency and to provide higher secrecy performance for physical layer security in beyond 5G networks.

To sum up, this thesis successfully addressed the challenges with computational complexity and spectral efficiency in 5G and beyond communication systems. With the developed algorithms and systems with recent emerging technologies proposed in this thesis work, it can be concluded that enhanced spectral efficiency performance and lower computational complexity were achieved.

5.2. Future Works

In this section, future works related to each of the thesis are summarized, followed by the potential future directions in 5G and beyond networks.

5.2.1. Extensions of the current works

Possible extensions of the current works of the thesis are presented as follows:

- **Practical MC and Experimental Validation:** In practice, MC changes with DoA of each incoming signal. Therefore, if one of the MC is known, higher DoA estimation accuracy can be achieved by employing the known MC as an initial coupling value in the calibration process. The proposed joint DoA-MC estimation in **Section 3.1** can be applied to the cases where there are groups of coherent signals arriving on the array from different directions. Moreover, by using different types of MCM, the proposed method can be extended to any arbitrary array structures including circular arrays. In **Section 3.2**, by using SDR, experimental verification of the multi-antenna NOMA system in the presence of mutual coupling and its compensation can be considered as an interesting future work.
- **Channel Impairment and Channel Fading:** In **Section 3.3**, practically, it is a challenging task to acquire the exact CSI in the mmWave channel due to the motion of the users. Therefore, adaptive user scheduling with channel prediction which considers the channel feedback delay and updated users conditions can be considered as future work. On the other hand, in **Section 3.5** and **Section 3.6**, it would be interesting to further tackle the issues related to power allocation, beamforming, and search algorithm for optimal OBRs/ORs, considering user fairness and practical wireless system conditions such as mutual coupling effects at the antenna array,

channel estimation errors or imperfect CSI, and time varying channel with Doppler effect. Moreover, in **Section 3.7**, since the proposed CoMP-NOMA network with RISs only considered Rayleigh fading channel with perfect CSI, it is a worthy research work to perform the analysis in different fading channel environments such as Rician and Nakagami fading with imperfect CSI.

- **Multi-antenna and Multi-user System:** In **Section 3.4**, it is an interesting idea to extend the current single-user CNN-BFNN to a multi-user beamforming network with hybrid beamforming and user scheduling. In addition, in **Section 3.5**, P-NOMA was performed in the system with a single-antenna BS. Therefore, by integrating P-NOMA in MIMO system with an efficient user scheduling and beamforming, the system sum-rate performance can be further enhanced, allowing it to be implemented in future wireless communication systems. Moreover, in **Section 3.6**, the proposed PB-NOMA can be extended for more than two groups with multiple users. In **Section 3.7**, multiple transmit antennas at the BSs can be also considered, by incorporating joint active and passive beamforming with multiple user clusters for improved capacity performance. In addition, instead of employing two RISs in the proposed CoMP-NOMA system in **Section 3.7**, sub-array of a single RIS can be optimized to simultaneously reflect the signals from the BSs in multi-cell networks.
- **Machine Learning:** It would be an interesting future work to efficiently utilize deep learning to train networks that can extract optimal overlapping ratios of the users in partial P-NOMA and PB-NOMA systems in **Section 3.5** and **Section 3.6** by maximizing the system spectral efficiency and energy efficiency via unsupervised learning. Moreover, optimal phase-shifts of the RISs in **Section 3.7** can be also determined by deep learning models.

5.2.2. Future directions

Possible future directions in 5G and beyond networks are described as follows:

- **Hybrid beamforming and NOMA:** Massive MIMO and NOMA systems with beamforming are important technologies for beyond 5G systems to utilize radio spectrum efficiently. However, acquiring channel state information and minimizing the interference power are some of the problems in producing very sharp beams.

Non-convex optimization problems of beamforming design are also challenging issues. Moreover, the demands on low cost and higher energy efficiency in wireless communication technologies lead to the studies of hybrid beamforming. Additionally, user scheduling and beam tracking is a critical task in multi-user scenarios of both OMA and NOMA systems to serve many users simultaneously while achieving user fairness, higher energy efficiency, higher data rate, and lower latency. Incorporating HB with reduced complexity and less power consumption in multiple access technologies offers higher multiplexing gains that results in higher spectral efficiency. Therefore, it is interesting to further study the optimization of hybrid beamforming integrated with multiple access technologies and also investigate robust user scheduling and beam tracking algorithms to support efficient beamforming and QoS requirements.

- **Applications of deep learning in HB-NOMA:** The advancement in Artificial Intelligent (AI) also helps to solve optimization problems more efficiently. It is expected that there will be many more applications of deep learning in the future. User scheduling in multi-user systems can be performed by learning to improve the system sum-rate or energy efficiency. Since user clustering and pairing in HB-NOMA is the first step in obtaining a nearly optimum hybrid beamformer without misalignment problem, a suitable deep learning method, which learns to group and pair the users according to different performance metrics and loss functions can be adopted. Furthermore, beam tracking can also be applied by learning the user information such as mobility, density, and traffic patterns; and predicting the next locations of the users. Moreover, adaptive subarray beamforming architecture can be designed using deep learning similar to the antenna selection via deep learning.
- **Physical Layer Security (PLS):** Due to the nature of radio frequency signals being broadcast in wireless communication systems, any wireless transmissions are prone to malicious network attacks such as eavesdropping, jamming, and spoofing. PLS has been gaining enormous attention by researchers since it is a promising solution to achieve better secrecy against eavesdropping attacks in NOMA networks. Unlike data encryption which requires heavy complexity, PLS techniques only exploit the characteristics of channels. Therefore, employing RISs in the systems can further improve secrecy performance by varying the channel conditions as desired.

In addition, along with RISs, Artificial Noise (AN) can be also exploited to decrease the SINR of the eavesdropper while increasing the SINR of the legitimate users in NOMA system. Therefore, solving non-convex optimization problems of joint active, passive, and AN beamforming that maximize secrecy rate is one of the challenges that should be focused as a future direction.

- **Unmanned Aerial Vehicle (UAV) Communication Networks:** Resource allocation including joint beamforming and trajectory design in RIS-assisted NOMA with UAV in CoMP network is also an interesting research direction. Due to LoS links and the flexible deployment of UAV, the main idea is to utilize UAV as either a transmitter or an RIS, based on the channel conditions and the QoS of cell-edge users, in addition to base station transmission for CoMP-NOMA in multi-cell networks. There are many open problems to be tackled in this scenario such as optimization for joint beamforming and RIS phase design, UAV location, user clustering and scheduling, and power allocation.

BIBLIOGRAPHY

- [1] H. Krim and M. Viberg, "Two decades of array signal processing research: the parametric approach," *IEEE Signal Processing Mag.*, vol. 13, no. 4, pp. 67–94, 1996, doi: 10.1109/79.526899.
- [2] A. Osseiran, V. Braun, T. Hidekazu, P. Marsch, H. Schotten, H. Tullberg, M. A. Uusitalo, and M. Schellman, "The foundation of the mobile and wireless communications system for 2020 and beyond: Challenges, enablers and technology solutions," in *2013 IEEE 77th Vehicular Technology Conference (VTC Spring)*, 2013, pp. 1–5, doi: 10.1109/VTCSpring.2013.6692781.
- [3] Z. Pi and F. Khan, "An introduction to millimeter-wave mobile broadband systems," *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 101–107, June 2011, doi: 10.1109/MCOM.2011.5783993.
- [4] T. S. Rappaport, S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. N. Wong, J. K. Schulz, M. Samimi, and F. Gutierrez, "Millimeter wave mobile communications for 5G cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, May 2013, doi: 10.1109/ACCESS.2013.2260813.
- [5] Y. Saito, Y. Kishiyama, A. Benjebbour, T. Nakamura, A. Li, and K. Higuchi, "Non-orthogonal multiple access (NOMA) for cellular future radio access," in *2013 IEEE 77th Vehicular Technology Conference (VTC Spring)*, 2013, pp. 1–5, doi: 10.1109/VTCSpring.2013.6692652.
- [6] Y. Liu, Z. Qin, M. El Kashlan, Z. Ding, A. Nallanathan, and L. Hanzo, "Non-orthogonal multiple access for 5G and beyond," *Proceedings of the IEEE*, vol. 105, no. 12, pp. 2347–2381, December 2017, doi: 10.1109/JPROC.2017.2768666.
- [7] M. S. Ali, E. Hossain, A. Al-Dweik, and D. I. Kim, "Downlink power allocation for CoMP-NOMA in multi-cell networks," *IEEE Trans. Commun.*, vol. 66, no. 9, pp. 3982–3998, April 2018, doi: 10.1109/TCOMM.2018.2831206.
- [8] L. Dai, B. Wang, Y. Yuan, S. Han, I. Chih-Lin, and Z. Wang, "Non-orthogonal multiple access for 5G: solutions, challenges, opportunities, and future research trends," *IEEE Commun. Mag.*, vol. 53, no. 9, pp. 74–81, September 2015, doi: 10.1109/MCOM.2015.7263349.
- [9] S. R. Islam, N. Avazov, O. A. Dobre, and K.-S. Kwak, "Power-domain non-orthogonal multiple access (NOMA) in 5G systems: Potentials and challenges," *IEEE Commun. Surv. Tutor.*, vol. 19, no. 2, pp. 721–742, October 2016, doi: 10.1109/COMST.2016.2621116.
- [10] F. Toşa, "Comparisons of beamforming techniques for 4G wireless communications systems," in *2010 IEEE 8th International Conference on Communications (ICC)*, 2010, pp. 271–274, doi: 10.1109/ICCOMM.2010.5509039.
- [11] M. Shehata, M. Helard, M. Crussiere, A. Roze, and C. Langlais, "Angular based beamforming and power allocation framework in a multi-user millimeter-wave massive MIMO system," in *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, 2018, pp. 1–6, doi: 10.1109/VTCSpring.2018.8417520.

- [12] R. Shafin and L. Liu, "Multi-cell multi-user massive FD-MIMO: downlink precoding and throughput analysis," *IEEE Trans. Wirel. Commun.*, vol. 18, no. 1, pp. 487–502, 2019, doi: 10.1109/TWC.2018.2882386.
- [13] L. Lu, G. Li, A. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: Benefits and challenges," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 742–758, 2014, doi: 10.1109/JSTSP.2014.2317671.
- [14] E. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, "Massive MIMO for next generation wireless systems," *IEEE Commun Mag.*, vol. 52, no. 2, pp. 186–195, 2014, doi: 10.1109/TASSP.1985.1164649.
- [15] X. Artiga, B. Devillers, and J. Perruisseau-Carrier, "Mutual coupling effects in multi-user massive MIMO base stations," in *2012 IEEE International Symposium on Antennas and Propagation*, 2012, pp. 1–2, doi: 10.1109/APS.2012.6349354.
- [16] M. K. Ozdemir, H. Arslan, and E. Arvas, "Mutual coupling effect in multi-antenna wireless communication systems," in *2003 IEEE Global Telecommunications Conference (IEEE Cat. No. 03CH37489)*, vol. 2, 2003, pp. 829–833, doi: 10.1109/GLOCOM.2003.1258355.
- [17] M. Ozdemir, E. Arvas, and H. Arslan, "Dynamics of spatial correlation and implications on MIMO systems," *IEEE Commun Magazine*, vol. 42, no. 6, pp. S14–S19, 2004, doi: 10.1109/MCOM.2004.1304227.
- [18] I. Stepanets, G. Fokin, and A. Müller, "Beamforming techniques performance evaluation for 5G massive MIMO systems," in *Collaborative Europ. Research Conf. (CERC)*, 2019, pp. 57–68, doi: 10.1109/ICSCN.2017.8085647.
- [19] Z. Ding, L. Dai, R. Schober, and H. V. Poor, "NOMA meets finite resolution analog beamforming in massive MIMO and millimeter-wave networks," *IEEE Commun. Lett.*, vol. 21, no. 8, pp. 1879–1882, May 2017, doi: 10.1109/LCOMM.2017.2700846.
- [20] W. Wu and D. Liu, "Non-orthogonal multiple access based hybrid beamforming in 5G mmwave systems," in *2017 IEEE 28th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2017, pp. 1–7, doi: 10.1109/PIMRC.2017.8292561.
- [21] X. Chen, Z. Zhang, C. Zhong, and D. W. K. Ng, "Exploiting multiple-antenna techniques for non-orthogonal multiple access," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 10, pp. 2207–2220, July 2017, doi: 10.1109/JSAC.2017.2724420.
- [22] M. A. Almasi and H. Mehrpouyan, "Non-orthogonal multiple access based on hybrid beamforming for mmwave systems," in *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, 2018, pp. 1–7, doi: 10.1109/VTC-Fall.2018.8690549.
- [23] T. Shan, M. Wax, and T. Kailath, "On spatial smoothing for direction-of-arrival estimation of coherent signals," *IEEE Trans. Acoust. Speech Signal Process.*, vol. 33, no. 4, pp. 806–811, 1985, doi: 10.1109/TASSP.1985.1164649.
- [24] S. Pillai and B. Kwon, "Forward/backward spatial smoothing techniques for coherent signal identification," *IEEE Trans. Acoust. Speech Signal Process.*, vol. 37, no. 1, pp. 8–15, 1989, doi: 10.1109/29.17496.

- [25] K. Hari and B. Ramakrishnan, "Performance analysis of a modified spatial smoothing technique for direction estimation," *Signal Process.*, vol. 79, no. 1, pp. 73–85, 1999, doi: 10.1016/S0165-1684(99)00081-X.
- [26] I. Gupta and A. Ksienski, "Effect of mutual coupling on the performance of adaptive arrays," *IEEE Trans. Antennas Propag.*, vol. 31, no. 5, pp. 785–791, 1983, doi: 10.1109/TAP.1983.1143128.
- [27] N. W. M. Thet, A. Kachroo, and M. K. Ozdemir, "Extended reduced-rank joint estimation of direction of arrival with mutual coupling for coherent signals," *Trans. on Emerging TeleCommun. Technologies*, p. e3620, 2019, doi: 10.1002/ett.3620.
- [28] T. Cover, "Broadcast channels," *IEEE Trans. Inf. Theory*, vol. 18, no. 1, pp. 2–14, 1972, doi: 10.1109/TIT.1972.1054727.
- [29] C. Kim, T. Kim, and J.-Y. Seol, "Multi-beam transmission diversity with hybrid beamforming for MIMO-OFDM systems," in *2013 IEEE Globecom Workshops (GC Wkshps)*, 2013, pp. 61–65, doi: 10.1109/GLOCOMW.2013.6824962.
- [30] B. Kim, W. Chung, S. Lim, S. Suh, J. Kwun, S. Choi, and D. Hong, "Uplink NOMA with multi-antenna," in *IEEE 81st International Conference on Vehicle Technology(VTC Spring)*, 2015, pp. 1–5, doi: 10.1109/VTC-Spring.2015.7146149.
- [31] Y. Li, K. An, T. Liang, and W. Lu, "Sum rate of multiuser large-scale MIMO in the presence of antenna correlation and mutual coupling," *Wireless Commun. and Mobile Comput.*, vol. 2019, June 2019, doi: 10.1155/2019/7985414.
- [32] C. Masouros, M. Sellathurai, and T. Ratnarajah, "Large-scale MIMO transmitters in fixed physical spaces: The effect of transmit correlation and mutual coupling," *IEEE Trans. Commun.*, vol. 61, no. 7, pp. 2794–2804, May 2013, doi: 10.1109/TCOMM.2013.052013.120440.
- [33] N. W. M. Thet, S. Khan, E. Arvas, and M. K. Özdemir, "Impact of mutual coupling on power-domain non-orthogonal multiple access (NOMA)," *IEEE Access*, vol. 8, pp. 188 401–188 414, 2020, doi: 10.1109/ACCESS.2020.3030110.
- [34] J. Choi, D. J. Love, and P. Bidigare, "Downlink training techniques for FDD massive MIMO systems: Open-loop and closed-loop training with memory," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 802–814, 2014, doi: 10.1109/JSTSP.2014.2313020.
- [35] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, "Scaling up MIMO: Opportunities and challenges with very large arrays," *IEEE Signal Process. Mag.*, vol. 30, no. 1, pp. 40–60, 2013, doi: 10.1109/MSP.2011.2178495.
- [36] N. W. M. Thet, T. Baykas, and M. K. Ozdemir, "Performance analysis of user scheduling in massive MIMO with fast moving users," in *2019 IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Commun. (PIMRC)*, 2019, pp. 1–6, doi: 10.1109/PIMRC.2019.8904133.
- [37] F. Sohrabi and W. Yu, "Hybrid digital and analog beamforming design for large-scale antenna arrays," *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 3, pp. 501–513, January 2016, doi: 10.1109/JSTSP.2016.2520912.

- [38] O. El Ayach, S. Rajagopal, S. Abu-Surra, Z. Pi, and R. W. Heath, "Spatially sparse precoding in millimeter wave MIMO systems," *IEEE Trans. Wireless Commun.*, vol. 13, no. 3, pp. 1499–1513, January 2014, doi: 10.1109/TWC.2014.011714.130846.
- [39] X. Yu, J.-C. Shen, J. Zhang, and K. B. Letaief, "Alternating minimization algorithms for hybrid precoding in millimeter wave MIMO systems," *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 3, pp. 485–500, February 2016, doi: 10.1109/JSTSP.2016.2523903.
- [40] N. W. M. Thet and M. K. Ozdemir, "Low-complexity deep learning-based beamforming in MISO systems," in *2021 29th Signal Processing and Communications Applications Conference (SIU)*, 2020, pp. 1–4.
- [41] —, "Joint overlap ratios and power allocation with user fairness in partial non-orthogonal multiple access (P-NOMA)," in *2020 28th Signal Processing and Communications Applications Conference (SIU)*, 2020, pp. 1–4, doi: 10.1109/SIU49456.2020.9302255.
- [42] J. Cui, Z. Ding, P. Fan, and N. Al-Dhahir, "Unsupervised machine learning-based user clustering in millimeter-wave-NOMA systems," *IEEE Trans. Wireless Commun.*, vol. 17, no. 11, pp. 7425–7440, September 2018, doi: 10.1109/TWC.2018.2867180.
- [43] H. Zeng, X. Zhu, Y. Jiang, Y. Zuo, Z. Wei, and T. Wang, "Fuzzy logic based multi-criterion user selection and resource allocation for green coordinated NOMA," in *2018 IEEE Global Communications Conference (GLOBECOM)*, 2018, pp. 1–6, doi: 10.1109/GLOCOM.2018.8648101.
- [44] E. Cabrera and R. Vesilo, "An enhanced K-means clustering algorithm with non-orthogonal multiple access (NOMA) for MMC networks," in *2018 28th Int. Telecommun. Netw. App. Conf. (ITNAC)*, Sydney, NSW, Australia, 2018, pp. 1–8, doi: 10.1109/ATNAC.2018.8615298.
- [45] B. Kimy, S. Lim, H. Kim, S. Suh, J. Kwun, S. Choi, C. Lee, S. Lee, and D. Hong, "Non-orthogonal multiple access in a downlink multiuser beamforming system," in *2013 IEEE Military Communications Conference (MILCOM)*, 2013, pp. 1278–1283, doi: 10.1109/MILCOM.2013.218.
- [46] M. Baghani, S. Parsaeefard, M. Derakhshani, and W. Saad, "Dynamic non-orthogonal multiple access (NOMA) and orthogonal multiple access (OMA) in 5G wireless networks," *IEEE Trans. Commun.*, May 2019, doi: 10.1109/TCOMM.2019.2919547.
- [47] B. Kim, Y. Park, and D. Hong, "Partial non-orthogonal multiple access (P-NOMA)," *IEEE Wireless Commun. Lett.*, May 2019, doi: 10.1109/LWC.2019.2918780.
- [48] N. W. M. Thet and M. K. Ozdemir, "Partial-beam non-orthogonal multiple access (PB-NOMA) with fuzzy clustering," *IEEE Wireless Commun. Lett.*, vol. 10, no. 6, pp. 1202–1206, 2021, doi: 10.1109/LWC.2021.3061779.
- [49] —, "Outage probability analysis of reconfigurable intelligent surface-enabled coordinated multi-points NOMA networks," *IEEE Trans. on Veh. Technol.*, [Under Review].

- [50] B. Friedlander and A. Weiss, "Direction finding in the presence of mutual coupling," *IEEE Trans. Antennas Propag.*, vol. 39, no. 3, pp. 273–284, 1991, doi: 10.1109/8.76322.
- [51] B. D. Van Veen and K. M. Buckley, "Beamforming: A versatile approach to spatial filtering," *IEEE ASSP Mag.*, vol. 5, no. 2, pp. 4–24, April 1988, doi:.
- [52] H. L. Van Trees, *Optimum array processing: Part IV of detection, estimation, and modulation theory*. John Wiley & Sons, 2004.
- [53] V. Krishnaveni, T. Kesavamurthy, and B. Aparna, "Beamforming for direction-of-arrival (DOA) estimation-a survey," *Int. J. Comput. Appl.*, vol. 61, no. 11, January 2013.
- [54] H. Singh and R. M. Jha, "Trends in adaptive array processing," *Int. J. Antennas. Propag.*, vol. 2012, November 2012.
- [55] S. Lee and Y. Lo, *Antenna Handbook: Theory, applications, and design*. Van Nostrand Reinhold, 1988.
- [56] C. A. Balanis, *Antenna theory: Analysis and design*. John Wiley & sons, 2016.
- [57] C. Vaidyanathan and K. M. Buckley, "Performance analysis of the MVDR spatial spectrum estimator," *IEEE Trans. Signal Process.*, vol. 43, no. 6, pp. 1427–1437, June 1995, doi:.
- [58] J. Capon, "High-resolution frequency-wavenumber spectrum analysis," *Proceedings of the IEEE*, vol. 57, no. 8, pp. 1408–1418, August 1969, doi: 10.1109/PROC.1969.7278.
- [59] G. Renzhou, "Suppressing radio frequency interferences with adaptive beam-former based on weight iterative algorithm," in *2007 IET Conf. Wireless Mobile Sensor Netw. (CCWMSN07)*. IET, 2007, pp. 648–651.
- [60] R. Schmidt, "Multiple emitter location and signal parameter estimation," *IEEE Trans. Antennas Propag.*, vol. 34, no. 3, pp. 276–280, March 1986, doi: 10.1109/TAP.1986.1143830.
- [61] R. Roy and T. Kailath, "ESPRIT-estimation of signal parameters via rotational invariance techniques," *IEEE Trans. Acoust. Speech Signal Process.*, vol. 37, no. 7, pp. 984–995, July 1989, doi:.
- [62] M. Aldababsa, M. Toka, S. Gökçeli, G. K. Kurt, and O. Kucur, "A tutorial on nonorthogonal multiple access for 5G and beyond," *Wireless Commun. and Mobile Comput.*, vol. 2018, June 2018, doi: 10.1155/2018/9713450.
- [63] S. Rangan, T. S. Rappaport, and E. Erkip, "Millimeter-wave cellular wireless networks: Potentials and challenges," *Proceedings of the IEEE*, vol. 102, no. 3, pp. 366–385, January 2014, doi: 10.1109/JPROC.2014.2299397.
- [64] A. Ghosh, T. A. Thomas, M. C. Cudak, R. Ratasuk, P. Moorut, F. W. Vook, T. S. Rappaport, G. R. MacCartney, S. Sun, and S. Nie, "Millimeter-wave enhanced local area systems: a high-data-rate approach for future wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1152–1163, June 2014, doi: 10.1109/JSAC.2014.2328111.
- [65] L. Zhu, J. Zhang, Z. Xiao, X. Cao, D. O. Wu, and X.-G. Xia, "Millimeter-wave NOMA with user grouping, power allocation and hybrid beamforming," *IEEE*

- Trans. Wireless Commun.*, vol. 18, no. 11, pp. 5065–5079, August 2019, doi: 10.1109/TWC.2019.2932070.
- [66] Z. Xiao, L. Dai, Z. Ding, J. Choi, and P. Xia, “Millimeter-wave communication with non-orthogonal multiple access for 5G,” [Online]. Available: <https://arxiv.org/abs/1709.07980>, 2017.
 - [67] S. A. R. Naqvi and S. A. Hassan, “Combining NOMA and mmWave technology for cellular communication,” in *IEEE 84th Vehicular Technology Conference (VTC-Fall)*, 2016, pp. 1–5, doi: 10.1109/VTCFall.2016.7880935.
 - [68] J. Li, X. Li, A. Wang, and N. Ye, “Performance analysis for downlink MIMO-NOMA in millimeter wave cellular network with D2D communications,” *Wireless Commun. and Mobile Comput.*, vol. 2019, January 2019, doi: 10.1155/2019/1914762.
 - [69] S. Henault, S. K. Podilchak, S. M. Mikki, and Y. M. Antar, “A methodology for mutual coupling estimation and compensation in antennas,” *IEEE Trans. Antennas Propagat.*, vol. 61, no. 3, pp. 1119–1131, November 2012, doi: 10.1109/TAP.2012.2229955.
 - [70] M. Wang, X. Ma, S. Yan, and C. Hao, “An autocalibration algorithm for uniform circular array with unknown mutual coupling,” *IEEE Antennas Propag. Lett.*, vol. 15, pp. 12–15, 2016, doi: 10.1109/LAWP.2015.2425423.
 - [71] H. Wu, C. Hou, H. Chen, W. Liu, and Q. Wang, “Direction finding and mutual coupling estimation for uniform rectangular arrays,” *Elsevier Signal Process.*, vol. 117, pp. 61 – 68, 2015, doi: 10.1016/j.sigpro.2015.04.019.
 - [72] N. W. M. Thet, M. K. Ozdemir, and A. Kachroo, “Reduced-rank joint estimation of DOA with mutual coupling,” in *2018 26th Signal Processing and Communications Applications Conference (SIU)*, 2018, pp. 1–4, doi: 10.1109/SIU.2018.8404592.
 - [73] H. Sajjad, S. Khan, and E. Arvas, “Mutual coupling reduction in array elements using (EBG) structures,” in *IEEE International Applied Computational Electromagnetics Society Symposium (ACES)*, 2017, doi: 10.23919/ROPACES.2017.7916410.
 - [74] T. Svantesson, “Modeling and estimation of mutual coupling in a uniform linear array of dipoles,” in *IEEE International Conference Acoustics, Speech and Signal Processing (ICASSP99)*, vol. 5, 1999, pp. 2961–2964, doi: 10.1109/ICASSP.1999.761384.
 - [75] C. Zhang, H. Huang, and B. Liao, “Direction finding in MIMO radar with unknown mutual coupling,” *IEEE Access*, vol. 5, pp. 4439–4447, 2017, doi: 10.1109/ACCESS.2017.2684465.
 - [76] P. Ioannides and C. A. Balanis, “Mutual coupling in adaptive circular arrays,” in *IEEE Antennas and Propagation Society International Symposium*, vol. 1, 2004, pp. 403–406, doi: 10.1109/APS.2004.1329659.
 - [77] J. Cui, Y. Liu, Z. Ding, P. Fan, and A. Nallanathan, “Optimal user scheduling and power allocation for millimeter wave NOMA systems,” *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1502–1517, 2018, doi: 10.1109/TWC.2017.2779504.

- [78] A. Alkhateeb, O. El Ayach, G. Leus, and R. W. Heath, "Channel estimation and hybrid precoding for millimeter wave cellular systems," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 831–846, July 2014, doi: 10.1109/JSTSP.2014.2334278.
- [79] S. Durrani and M. E. Bialkowski, "Effect of mutual coupling on the interference rejection capabilities of linear and circular arrays in CDMA systems," *IEEE Trans. Antennas Propagat.*, vol. 52, no. 4, pp. 1130–1134, May 2004, doi: 10.1109/TAP.2004.825640.
- [80] M. S. Islam, T. Jessy, M. S. Hassan, K. Mondal, and T. Rahman, "Suitable beamforming technique for 5G wireless communications," in *2016 Int. Conf. Comput. Commun. Auto. (ICCCA)*, April 2016, pp. 1554–1559, doi:.
- [81] A. J. Paulraj and T. Kailath, "Increasing capacity in wireless broadcast systems using distributed transmission/directional reception (dtdr)," Sep. 6 1994, uS Patent 5,345,599.
- [82] G. J. Foschini, "Layered space-time architecture for wireless communication in a fading environment when using multi-element antennas," *Bell Labs Technical J.*, vol. 1, no. 2, pp. 41–59, June 1996.
- [83] S. M. Alamouti, "A simple transmit diversity technique for wireless communications," *IEEE J. Sel. Areas Commun.*, October 1998, doi:.
- [84] V. Tarokh, N. Seshadri, and A. R. Calderbank, "Space-time codes for high data rate wireless communication: Performance criterion and code construction," *IEEE Trans. Inf. Theory*, vol. 44, no. 2, pp. 744–765, March 1998, doi:.
- [85] V. Tarokh, H. Jafarkhani, and A. R. Calderbank, "Space-time block codes from orthogonal designs," *IEEE Trans. Inf. Theory*, vol. 45, no. 5, pp. 1456–1467, July 1999, doi:.
- [86] E. Ali, M. Ismail, R. Nordin, and N. F. Abdulah, "Beamforming techniques for massive MIMO systems in 5G: overview, classification, and trends for future research," *Front. Inform. Tech. El.*, vol. 18, no. 6, pp. 753–772, June 2017, doi: 10.1016/j.compeleceng.2017.04.029.
- [87] W. Roh, J.-Y. Seol, J. Park, B. Lee, J. Lee, Y. Kim, J. Cho, K. Cheun, and F. Aryanfar, "Millimeter-wave beamforming as an enabling technology for 5G cellular communications: Theoretical feasibility and prototype results," *IEEE Commun. Mag.*, vol. 52, no. 2, pp. 106–113, February 2014, doi:.
- [88] M. Li, Z. Wang, H. Li, Q. Liu, and L. Zhou, "A hardware-efficient hybrid beamforming solution for mmwave MIMO systems," *IEEE Wireless Communications*, vol. 26, no. 1, pp. 137–143, January 2019, doi:.
- [89] S. Payami, M. Ghorashi, M. Dianati, and M. Sellathurai, "Hybrid beamforming with a reduced number of phase shifters for massive MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 4843–4851, February 2018, doi:.
- [90] Z. Wang, M. Li, H. Li, and Q. Liu, "Hybrid beamforming with one-bit quantized phase shifters in mmwave MIMO systems," in *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1–6, doi:.
- [91] R. Méndez-Rial, C. Rusu, N. González-Prelcic, A. Alkhateeb, and R. W. Heath, "Hybrid MIMO architectures for millimeter wave communications: Phase shifters or switches?" *IEEE Access*, vol. 4, pp. 247–267, January 2016, doi:.

- [92] F. Sohrabi and W. Yu, "Hybrid beamforming with finite-resolution phase shifters for large-scale MIMO systems," in *2015 IEEE 16th Int. Work. Signal Process. Adv. Wireless Commun. (SPAWC)*, 2015, pp. 136–140, doi:.
- [93] S. Kutty and D. Sen, "Beamforming for millimeter wave communications: An inclusive survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 2, pp. 949–973, December 2015, doi:.
- [94] T. E. Bogale, L. B. Le, A. Haghighat, and L. Vandendorpe, "On the number of RF chains and phase shifters, and scheduling design with hybrid analog–digital beamforming," *IEEE Trans. Wireless Commun.*, vol. 15, no. 5, pp. 3311–3326, January 2016, doi:.
- [95] S. Hur, T. Kim, D. J. Love, J. V. Krogmeier, T. A. Thomas, and A. Ghosh, "Millimeter wave beamforming for wireless backhaul and access in small cell networks," *IEEE Trans. Commun.*, vol. 61, no. 10, pp. 4391–4403, September 2013, doi:.
- [96] I. Ahmed, H. Khammari, A. Shahid, A. Musa, K. S. Kim, E. De Poorter, and I. Moerman, "A survey on hybrid beamforming techniques in 5G: Architecture and system model perspectives," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 4, pp. 3060–3097, June 2018, doi:.
- [97] J. Cai, B. Rong, and S. Sun, "A low complexity hybrid precoding scheme for massive MIMO system," in *2016 16th Int. Symp. Commun. Inf. Tech. (ISCIT)*, 2016, pp. 638–641, doi:.
- [98] E. Björnson, M. Bengtsson, and B. Ottersten, "Optimal multiuser transmit beamforming: A difficult problem with a simple solution structure [lecture notes]," *IEEE Signal Process. Mag.*, vol. 31, no. 4, pp. 142–148, June 2014, doi:.
- [99] H. Yang and T. L. Marzetta, "Performance of conjugate and zero-forcing beamforming in large-scale antenna systems," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 2, pp. 172–179, January 2013, doi:.
- [100] C. B. Peel, B. M. Hochwald, and A. L. Swindlehurst, "A vector-perturbation technique for near-capacity multiantenna multiuser communication-part I: channel inversion and regularization," *IEEE Transactions on Communications*, vol. 53, no. 1, pp. 195–202, January 2005, doi:.
- [101] T. E. Bogale and L. B. Le, "Beamforming for multiuser massive MIMO systems: Digital versus hybrid analog-digital," in *2014 IEEE Glob. Commun. Conf.*, 2014, pp. 4066–4071, doi:.
- [102] S. Han, I. Chih-Lin, Z. Xu, and C. Rowell, "Large-scale antenna systems with hybrid analog and digital beamforming for millimeter wave 5G," *IEEE Commun. Mag.*, vol. 53, no. 1, pp. 186–194, January 2015, doi:.
- [103] A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. L. H. Nguyen, L. Li, and K. Haneda, "Hybrid beamforming for massive MIMO: A survey," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 134–141, September 2017, doi:.
- [104] S. Han, I. Chih-Lin, and Z. Xu, "Reference signals design for hybrid analog and digital beamforming," *IEEE Commun. Lett.*, vol. 18, no. 7, pp. 1191–1193, April 2014, doi:.

- [105] Y. Lu, C. Cheng, J. Yang, and G. Gui, "Improved hybrid precoding scheme for mmwave large-scale MIMO systems," *IEEE Access*, vol. 7, pp. 12 027–12 034, January 2019, doi: .
- [106] J. Nam, A. Adhikary, J.-Y. Ahn, and G. Caire, "Joint spatial division and multiplexing: Opportunistic beamforming, user grouping and simplified downlink scheduling," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 876–890, 2014, doi: 10.1109/JSTSP.2014.2313808.
- [107] D. A. Gore, R. W. Heath, and A. J. Paulraj, "Transmit selection in spatial multiplexing systems," *IEEE Commun. Lett.*, vol. 6, no. 11, pp. 491–493, 2002, doi: 10.1109/LCOMM.2002.805517.
- [108] A. Adhikary, J. Nam, J.-Y. Ahn, and G. Caire, "Joint spatial division and multiplexing—the large-scale array regime," *IEEE Trans. Inf. Theory*, vol. 59, no. 10, pp. 6441–6463, June 2013, doi: 10.1109/TIT.2013.2269476.
- [109] Y. Xu, G. Yue, N. Prasad, S. Rangarajan, and S. Mao, "User grouping and scheduling for large scale MIMO systems with two-stage precoding," in *2014 IEEE International Conference on Communications (ICC)*, 2014, pp. 5197–5202, doi: 10.1109/ICC.2014.6884146.
- [110] Y. Xu², G. Yue, N. Prasad, S. Rangarajan, and S. Mao, "User grouping and scheduling for large scale MIMO systems with two-stage precoding," in *IEEE International Conference on Communications (ICC)*, 2014, pp. 5197–5202, doi: 10.1109/ICC.2014.6884146.
- [111] T. Yoo and A. Goldsmith, "On the optimality of multiantenna broadcast scheduling using zero-forcing beamforming," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 3, pp. 528–541, 2006, doi: 10.1109/JSAC.2005.862421.
- [112] B. Kim, S. Lim, H. Kim, S. Suh, J. Kwun, S. Choi, C. Lee, S. Lee, and D. Hong, "Non-orthogonal multiple access in a downlink multiuser beamforming system," in *IEEE Military Communications Conference (MILCOM)*, 2013, pp. 1278–1283, doi: 10.1109/MILCOM.2013.218.
- [113] A. Paulraj, R. Roy, and T. Kailath, "Estimation of signal parameters via rotational invariance techniques-ESPRIT," in *1985 IEEE 9th Asilomar Conference on Circuits, Systems and Computers (ACSC'85)*, 1985, doi: 10.1109/MILCOM.1986.4805850.
- [114] S. Poormohammad and F. Farzaneh, "Precision of direction of arrival (DOA) estimation using novel three dimensional array geometries," *AEU Int. J. Electron. Commun.*, vol. 75, pp. 35–45, 2017, doi: 10.1016/j.aeue.2017.02.013.
- [115] L. Wang, R. de Lamare, and M. Haardt, "Direction finding algorithms based on joint iterative subspace optimization," *IEEE Trans. Aerosp Electron Syst.*, vol. 50, no. 4, pp. 2541–2553, 2014, doi: 10.1109/TAES.2014.120395.
- [116] L. Qiu, Y. Cai, R. de Lamare, and M. Zhao, "Reduced-rank DOA estimation algorithms based on alternating low-rank decomposition," *IEEE Signal Process Lett.*, vol. 23, no. 5, pp. 565–569, 2016, doi: 10.1109/LSP.2016.2541688.
- [117] P. Fletcher, M. Dean, and A. Nix, "Mutual coupling in multi-element array antennas and its influence on MIMO channel capacity," *Electronics Lett.*, vol. 39, no. 4, pp. 342–344, February 2003, doi: 10.1049/el:20030219.

- [118] B. Clerckx, C. Craeye, D. Vanhoenacker-Janvier, and C. Oestges, "Impact of antenna coupling on 2×2 MIMO communications," *IEEE Trans. Veh. Technol.*, vol. 56, no. 3, pp. 1009–1018, May 2007, doi: 10.1109/TVT.2007.895545.
- [119] H. D. Nguyen, X. Wang, and H. T. Hui, "Mutual coupling and transmit correlation: Impact on the sum-rate capacity of the two-user MISO broadcast channels," in *2011 IEEE International Symposium on Antennas and Propagation (AP-SURSI)*, 2011, pp. 63–66, doi: 10.1109/APS.2011.5996383.
- [120] X. Liu and M. E. Bialkowski, "Effect of antenna mutual coupling on MIMO channel estimation and capacity," *Int. J. Antennas Propagat.*, vol. 2010, January 2010, doi: 10.1155/2010/306173.
- [121] R. Fallahi and M. Roshandel, "Effect of mutual coupling and configuration of concentric circular array antenna on the signal-to-interference performance in CDMA systems," *Progress In Electromagn. Research*, vol. 76, pp. 427–447, 2007, doi: 10.2528/PIER07070104.
- [122] S. Akkar, F. Harabi, and A. Gharsallah, "Directions of arrival estimation with planar antenna arrays in the presence of mutual coupling," *Int. J. Electronics*, vol. 100, no. 6, pp. 818–836, June 2013, doi: 10.1080/00207217.2012.720956.
- [123] C. Qi, Y. Wang, Y. Zhang, and H. Chen, "DOA estimation and self-calibration algorithm for uniform circular array," *Electron Lett*, vol. 41, no. 20, pp. 1092–1094, 2005, doi: 10.1049/el:20051577.
- [124] F. Sellone and A. Serra, "A novel online mutual coupling compensation algorithm for uniform and linear arrays," *IEEE Trans. Signal Process*, vol. 55, no. 2, pp. 560–573, 2007, doi: 10.1109/TSP.2006.885732.
- [125] G. Jiang, Y. Dong, X. Mao, and Y. Liu, "Improved 2D direction of arrival estimation with a small number of elements in uca in the presence of mutual coupling," *AEU Int. J. Electron. Commun.*, vol. 71, pp. 131–138, 2017, doi: 10.1016/j.aeue.2016.10.012.
- [126] M. Shaghghi and S. A. Vorobyov, "Subspace leakage analysis and improved DOA estimation with small sample size," *IEEE Trans. Signal Process*, vol. 63, no. 12, pp. 3251–3265, 2015, doi: 10.1109/TSP.2015.2422675.
- [127] H. Zhou, G. Hu, J. Shi, and Z. Feng, "Orthogonal projection method for DOA estimation in low-altitude environment based on signal subspace," *AEU Int. J. Electron. Commun.*, vol. 83, pp. 317–321, 2018, doi: 10.1016/j.aeue.2017.09.021.
- [128] J. Dai and Z. Ye, "Spatial smoothing for direction of arrival estimation of coherent signals in the presence of unknown mutual coupling," *IET Signal Process*, vol. 5, no. 4, pp. 418–425, 2011, doi: 10.1049/iet-spr.2008.0100.
- [129] B. Liao and S.-C. Chan, "DOA estimation of coherent signals for uniform linear arrays with mutual coupling," in *2011 IEEE International Symposium of Circuits and Systems (ISCAS)*, 2011, pp. 377–380, doi: 10.1109/LAWP.2014.2343671.
- [130] H. Shi, Z. Li, D. Liu, and H. Chen, "Efficient method of two-dimensional DOA estimation for coherent signals," *EURASIP J. Wirel. Commun. Netw.*, vol. 2017, no. 1, p. 53, 2017, doi: 10.1186/s13638-017-0835-1.

- [131] J. Shi, G. Hu, F. Sun, B. Zong, and X. Wang, "Improved spatial differencing scheme for 2-D DOA estimation of coherent signals with uniform rectangular arrays," *Sensors*, vol. 17, no. 9, p. 1956, 2017, doi: 10.3390/s17091956.
- [132] C. Qi, Z. Chen, Y. Wang, and Y. Zhang, "DOA estimation for coherent sources in unknown nonuniform noise fields," *IEEE Trans. Aerospace and Electronic Systems*, vol. 43, no. 3, pp. 1195–1204, 2007, doi: 10.3390/s17091956.
- [133] D. Ha, K. Lee, and J. Kang, "Energy efficiency analysis with circuit power consumption in massive MIMO systems," in *2013 IEEE 24th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2013, pp. 938–942, doi: 10.1109/PIMRC.2013.6666272.
- [134] A. Alkhateeb and R. W. Heath, "Frequency selective hybrid precoding for limited feedback millimeter wave systems," *IEEE Trans. Commun.*, vol. 64, no. 5, pp. 1801–1818, April 2016, doi: 10.1109/TCOMM.2016.2549517.
- [135] Y.-S. Jeon and M. Min, "Large system analysis of two-stage beamforming with limited feedback in FDD massive MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 4984–4997, March 2018, doi: 10.1109/TVT.2018.2817563.
- [136] O. Bai, H. Gao, T. Lv, and C. Yuen, "Low-complexity user scheduling in the downlink massive MU-MIMO system with linear precoding," in *IEEE/CIC Int. Conf. on Communications in China (ICCC)*, 2014, pp. 380–384, doi: 10.1109/ICCCChina.2014.7008306.
- [137] S. Dierks and N. Juenger, "Scheduling for massive MIMO with few excess antennas," in *VDE 20th International ITG Workshop on Smart Antennas (WSA)*, 2016, pp. 1–5, doi: .
- [138] Y. Sun, S. Lv, S. Liu, and Y. H. Zhang, "Joint user scheduling and power allocation for massive MIMO downlink with two-stage precoding," in *2nd IEEE Int. Conf. Comput. Commun. (ICCC)*, 2016, pp. 2917–2921, doi: 10.1109/CompComm.2016.7925231.
- [139] M. Kuerbis, N. M. Balasubramanya, L. Lampe, and A. Lampe, "User scheduling in massive MIMO systems with a large number of devices," in *IEEE 28th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, October 2017, pp. 1–6, doi: 10.1109/PIMRC.2017.8292733.
- [140] T. E. Bogale, X. Wang, and L. B. Le, "Adaptive channel prediction, beamforming and scheduling design for 5G V2I network," in *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall)*, 2017, pp. 1–5, doi: 10.1109/VTC-Fall.2017.8288275.
- [141] C. Lv, J.-C. Lin, and Z. Yang, "Channel prediction for millimeter wave MIMO-OFDM commun. in rapidly time-varying frequency-selective fading channels," *IEEE Access*, vol. 7, pp. 15 183–15 195, 2019, doi: 10.1109/ACCESS.2019.2893619.
- [142] W. Xia, G. Zheng, Y. Zhu, J. Zhang, J. Wang, and A. P. Petropulu, "A deep learning framework for optimization of MISO downlink beamforming," *arXiv preprint arXiv:1901.00354*, January 2019, doi: 10.1109/TCOMM.2019.2960361.

- [143] H. Huang, W. Xia, J. Xiong, J. Yang, G. Zheng, and X. Zhu, "Unsupervised learning-based fast beamforming design for downlink MIMO," *IEEE Access*, vol. 7, pp. 7599–7605, December 2018, doi: 10.1109/TWC.2018.2867180.
- [144] T. Lin and Y. Zhu, "Beamforming design for large-scale antenna arrays using deep learning," *arXiv preprint arXiv:1904.03657*, June 2019. [Online]. Available: <https://arxiv.org/abs/1904.03657v2>
- [145] H. Huang, Y. Song, J. Yang, G. Gui, and F. Adachi, "Deep-learning-based millimeter-wave massive MIMO for hybrid precoding," *IEEE Trans. Veh. Technol.*, January 2019, doi: 10.1109/TVT.2019.2893928.
- [146] N. Qian, "On the momentum term in gradient descent learning algorithms," *Neural networks*, vol. 12, no. 1, pp. 145–151, January 1999, doi: 10.1016/S0893-6080(98)00116-6.
- [147] T. Greenberg-Toledo, R. Mazar, A. Haj-Ali, and S. Kvatinsky, "Supporting the momentum training algorithm using a memristor-based synapse," *IEEE Trans. Circu. Syst. I: Regular Papers*, vol. 66, no. 4, pp. 1571–1583, January 2019, doi: 10.1109/TCSI.2018.2888538.
- [148] T. Xie, L. Dai, X. Gao, M. Z. Shakir, and J. Li, "Geometric mean decomposition based hybrid precoding for millimeter-wave massive MIMO," *China Commun.*, vol. 15, no. 5, pp. 229–238, June 2018, doi: 10.1109/CC.2018.8388000.
- [149] H. J. Kwon, J. H. Lee, and W. Choi, "Machine learning-based beamforming in two-user MISO interference channels," in *2019 Int. Conf. Artif. Intel. Inf. Commun. (ICAIIIC)*, 2019, pp. 496–499, doi: 10.1109/ICAIIIC.2019.8669027.
- [150] F. Sohrabi and W. Yu, "Hybrid analog and digital beamforming for mmwave OFDM large-scale antenna arrays," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 7, pp. 1432–1443, April 2017, doi: 10.1109/JSAC.2017.2698958.
- [151] S. Ali, E. Hossain, and D. I. Kim, "Non-orthogonal multiple access (NOMA) for downlink multiuser MIMO systems: User clustering, beamforming, and power allocation," *IEEE Access*, vol. 5, pp. 565–577, December 2016, doi: 10.1109/ACCESS.2016.2646183.
- [152] W. Hao, M. Zeng, Z. Chu, and S. Yang, "Energy-efficient power allocation in millimeter wave massive MIMO with non-orthogonal multiple access," *IEEE Wireless Commun. Lett.*, vol. 6, no. 6, pp. 782–785, August 2017, doi: 10.1109/LWC.2017.2741493.
- [153] J. Cui, Y. Liu, Z. Ding, P. Fan, and A. Nallanathan, "Optimal user scheduling and power allocation for millimeter wave NOMA systems," *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 1502–1517, December 2017, doi: 10.1109/TWC.2017.2779504.
- [154] Z. Wei, L. Zhao, J. Guo, D. W. K. Ng, and J. Yuan, "A multi-beam NOMA framework for hybrid mmwave systems," in *2018 IEEE International Conference on Communications (ICC)*, 2018, pp. 1–7, doi: 10.1109/ICC.2018.8422365.
- [155] F. Xu, X. Yu, M. Li, and B. Wen, "Energy-efficient power allocation scheme for hybrid precoding mmwave-NOMA system with multi-user pairing," in *2019 IEEE International Conference on Communications Workshops (ICC Workshops)*, 2019, pp. 1–5, doi:.

- [156] X. Yu, F. Xu, K. Yu, and X. Dang, "Power allocation for energy efficiency optimization in multi-user mmwave-NOMA system with hybrid precoding," *IEEE Access*, August 2019, doi: 10.1109/ACCESS.2019.2933328.
- [157] Z. Wei, D. W. K. Ng, and J. Yuan, "NOMA for hybrid mmwave communication systems with beamwidth control," *IEEE J. Sel. Topics Signal Process.*, vol. 13, no. 3, pp. 567–583, February 2019, doi: 10.1109/JSTSP.2019.2901593.
- [158] Z. Wei, L. Zhao, J. Guo, D. W. K. Ng, and J. Yuan, "Multi-beam NOMA for hybrid mmwave systems," *IEEE Transactions on Communications*, vol. 67, no. 2, pp. 1705–1719, November 2018, doi: 10.1109/TCOMM.2018.2879930.
- [159] Z. Wei, J. Guo, D. W. K. Ng, and J. Yuan, "Fairness comparison of uplink NOMA and OMA," in *2017 IEEE 85th Vehicular Technology Conference. (VTC Spring)*, 2017, pp. 1–6, doi: 10.1109/VTCSpring.2017.8108680.
- [160] B. Kim, J. Heo, and D. Hong, "Partial non-orthogonal multiple access (P-NOMA) with respect to user fairness," in *2019 IEEE 90th Vehicular Technology Conference. (VTC Fall)*, 2019, pp. 1–5, doi: 10.1109/VTCTFall.2019.8891478.
- [161] F. Fang, H. Zhang, J. Cheng, and V. C. Leung, "Energy-efficient resource allocation for downlink non-orthogonal multiple access network," *IEEE Trans. Commun.*, vol. 64, no. 9, pp. 3722–3732, July 2016, doi: 10.1109/TCOMM.2016.2594759.
- [162] E. Basar, M. Di Renzo, J. De Rosny, M. Debbah, M.-S. Alouini, and R. Zhang, "Wireless communications through reconfigurable intelligent surfaces," *IEEE access*, vol. 7, pp. 116 753–116 773, August 2019, doi: 10.1109/ACCESS.2019.2935192.
- [163] E. Björnson, Ö. Özdogan, and E. G. Larsson, "Intelligent reflecting surface versus decode-and-forward: How large surfaces are needed to beat relaying?" *IEEE Wireless Commun. Lett.*, vol. 9, no. 2, pp. 244–248, October 2019, doi: 10.1109/LWC.2019.2950624.
- [164] Q. Wu and R. Zhang, "Towards smart and reconfigurable environment: Intelligent reflecting surface aided wireless network," *IEEE Commun. Mag.*, vol. 58, no. 1, pp. 106–112, November 2019, doi: 10.1109/MCOM.001.1900107.
- [165] Z. Ding and H. V. Poor, "A simple design of IRS-NOMA transmission," *IEEE Commun. Lett.*, vol. 24, no. 5, pp. 1119–1123, February 2020, doi: 10.1109/LCOMM.2020.2974196.
- [166] T. Hou, Y. Liu, Z. Song, X. Sun, Y. Chen, and L. Hanzo, "Reconfigurable intelligent surface aided NOMA networks," *IEEE J. Sel. Area Commun.*, vol. 38, no. 11, pp. 2575–2588, July 2020, doi: 10.1109/JSAC.2020.3007039.
- [167] X. Yue and Y. Liu, "Performance analysis of intelligent reflecting surface assisted NOMA networks," *arXiv preprint arXiv:2002.09907*, 2020.
- [168] A.-A. A. Boulogeorgos and A. Alexiou, "Performance analysis of reconfigurable intelligent surface-assisted wireless systems and comparison with relaying," *IEEE Access*, vol. 8, pp. 94 463–94 483, May 2020, doi: 10.1109/ACCESS.2020.2995435.
- [169] G. T. . V11.0.0, "Coordinated multi-point operation for LTE," *3GPP TSG RAN WG1*, September 2016.

- [170] W. Shin, M. Vaezi, B. Lee, D. J. Love, J. Lee, and H. V. Poor, "Non-orthogonal multiple access in multi-cell networks: theory, performance, and practical challenges," *IEEE Commun. Mag.*, vol. 55, no. 10, pp. 176–183, August 2017, doi: 10.1109/MCOM.2017.1601065.
- [171] Z. Yang, C. Pan, W. Xu, Y. Pan, M. Chen, and M. El Kashlan, "Power control for multi-cell networks with non-orthogonal multiple access," *IEEE Trans. Wirel. Commun.*, vol. 17, no. 2, pp. 927–942, November 2017, doi: 10.1109/TWC.2017.2772824.
- [172] M. Elhattab, M. A. Arfaoui, C. Assi, and A. Ghayeb, "Reconfigurable intelligent surface assisted coordinated multipoint in downlink NOMA networks," *IEEE Commun. Lett.*, vol. 25, no. 2, pp. 1119–1123, February 2021, doi: 10.1109/LCOMM.2020.3029717.
- [173] A. Kachroo, "Joint estimation of direction of arrival with unknown mutual coupling in massive MIMO networks and LTE radio resource block allocation optimization in maritime channels," Master's thesis, Electronic and Computer Engineering, Istanbul Şehir University, 2017.
- [174] S. Boyd and L. Vandenberghe, *Convex optimization*. Cambridge university press, 2004.
- [175] S. Haykin, *Adaptive Filter Theory*. London, UK: Pearson Higher Education, 2013.
- [176] S. Khan, H. Sajjad, M. K. Ozdemir, and E. Arvas, "Mutual coupling compensation in transmitting arrays of thin wire antennas," *Appl. Comput. Electromagn. Soc. J. (ACES Journal)*, vol. 33, no. 11, pp. 1182–1189, Nov 2018.
- [177] S. Khan², H. Sajjad, M. K. Ozdemir, and E. Arvas, "Mutual coupling compensation in receiving antenna arrays," in *IEEE International Applied Computational Electromagnetics Society Symposium (ACES)*, 2020, doi: 10.23919/ACES49320.2020.9196181.
- [178] G. Lee, Y. Sung, and J. Seo, "Randomly-directional beamforming in millimeter-wave multiuser MISO downlink," *IEEE Trans. Wirel. Commun.*, vol. 15, no. 2, pp. 1086–1100, September 2015, doi: 10.1109/TWC.2015.2483493.
- [179] M. N. Kulkarni, A. Ghosh, and J. G. Andrews, "A comparison of MIMO techniques in downlink millimeter wave cellular networks with hybrid beamforming," *IEEE Trans. Commun.*, vol. 64, no. 5, pp. 1952–1967, March 2016, doi: 10.1109/TCOMM.2016.2542825.
- [180] S. Khan, H. Sajjad, M. K. Ozdemir, and E. Arvas, "Mutual coupling compensation in receiving arrays and its implementation on software defined radios," in *IEEE International Applied Computational Electromagnetics Society Symposium (ACES)*, 2020, doi: 10.23919/ACES49320.2020.9196055.
- [181] Z. Li, S. Han, S. Sangodoyin, R. Wang, and A. F. Molisch, "Joint optimization of hybrid beamforming for multi-user massive MIMO downlink," *IEEE Trans. Wireless Commun.*, vol. 17, no. 6, pp. 3600–3614, 2018, doi: 10.1109/TWC.2018.2808523.

- [182] A. Adhikary, E. Al Safadi, M. K. Samimi, R. Wang, G. Caire, T. S. Rappaport, and A. F. Molisch, "Joint spatial division and multiplexing for mm-wave channels," *IEEE Journal on Selected Areas in Commun.*, vol. 32, no. 6, pp. 1239–1255, 2014, doi: 10.1109/JSAC.2014.2328173.
- [183] I. A. Hemadeh, K. Satyanarayana, M. El-Hajjar, and L. Hanzo, "Millimeter-wave communications : physical channel models, design considerations, antenna constructions, and link-budget," *IEEE Commun. Surveys & Tutorials*, vol. 20, no. 2, pp. 870–913, 2017, doi: 10.1109/COMST.2017.2783541.
- [184] M. Kulin, T. Kazaz, I. Moerman, and E. De Poorter, "End-to-end learning from spectrum data: A deep learning approach for wireless signal identification in spectrum monitoring applications," *IEEE Access*, vol. 6, pp. 18 484–18 501, 2018, doi: 10.1109/ACCESS.2018.2818794.
- [185] T. Lin and Y. Zhu, "Dataset of beamforming design for large-scale antenna arrays using deep learning," <https://drive.google.com/drive/folders/1XT3JP3SvSIYrb4Nt4SJgXCMagvgfJuSy?usp=sharing>, 2019.
- [186] R. K. Jain, D.-M. W. Chiu, and W. R. Hawe, "A quantitative measure of fairness and discrimination for resource allocation in shared computer systems," *ACM Trans. on Comput. Syst.*, September 1984.
- [187] T. Manglayev, R. C. Kizilirmak, and Y. H. Kho, "Optimum power allocation for non-orthogonal multiple access (NOMA)," in *2016 IEEE 10th International Conference on Application of Information and Communication Technologies (AICT)*, 2016, pp. 1–4, doi: 10.1109/TWC.2018.2876526.
- [188] M. Sato and Y. Sato, "Fuzzy clustering model for fuzzy data," in *1995 IEEE International Conference on Fuzzy Systems*, vol. 4, 1995, pp. 2123–2128, doi: 10.1109/FUZZY.1995.409973.
- [189] J. Proakis and M. Salehi, *Digital communications 5th ed.* New York,: McGraw-Hill, 2007.
- [190] P. Stoica and A. Gershman, "Maximum-likelihood DOA estimation by data-supported grid search," *IEEE Signal Process Lett*, vol. 6, no. 10, pp. 273–275, 1999, doi: 10.1109/97.789608.
- [191] J. Yang, W. Ryoo, W. Sung, J.-H. Kim, and J. Park, "3D antenna structures using uniform triangular arrays for efficient full-directional multiuser transmission," *Int. J Antennas Propagat.*, vol. 2019, November 2019, doi: 10.1109/APS.2004.1329659.
- [192] A. Zakeri, N. Mokari, and H. Yanikomeroğlu, "Joint radio resource allocation and 3D beam-forming in MISO-NOMA-based network with profit maximization for mobile virtual network operators," [Online]. Available: <https://arxiv.org/abs/1907.05161>, 2019.
- [193] Z. Qin, H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep learning in physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 2, pp. 93–99, 2019, doi: 10.1109/MWC.2019.1800601.
- [194] R. Hunger, *Floating Point Operations in Matrix-Vector Calculus.* Technische Universität München, München, Germany, 2005.

APPENDIX A

Appendix A1 Proof of PB-NOMA sum-rate

Using the reduced NOR $\alpha_g - \epsilon_{g'}$ and letting $a = \Delta_s M$, sum-rates in the proposed system can be written as

$$S_{g,f} \approx a(1 - \alpha_g + \epsilon_{g'}) \log_2 \left(1 + \frac{P_{gf}}{\hat{P}_{gf} + \sigma^2} \right) + a(\alpha_g - \epsilon_{g'} + \beta) \log_2 \left(1 + \frac{(1 - \gamma)P_{gf}}{\gamma P_{gf} + \hat{P}_{gf} + \sigma^2} \right) \quad (\text{A1.1})$$

$$\begin{aligned} S_{g,n} \approx & a(1 - \beta) \log_2 \left(1 + \frac{P_{gn}}{\hat{P}_{gn} + \sigma^2} \right) + a(\alpha_g - \epsilon_{g'} + \beta) \log_2 \left(1 + \frac{\gamma P_{gn}}{\hat{P}_{gn} + \sigma^2} \right) \\ & + a\epsilon_{g'} \log_2 \left(1 + \frac{\gamma P_{g'_n}}{\hat{P}_{g'_n} + \sigma^2} \right) + a\epsilon_{g'} \log_2 \left(1 + \frac{(1 - \gamma)\hat{P}_{gn}}{\gamma \hat{P}_{gn} + P_{gn} + \sigma^2} \right) \\ & - a\epsilon_{g'} \log_2 \left(1 + \frac{P_{g'_n}}{\hat{P}_{g'_n} + \sigma^2} \right) \end{aligned} \quad (\text{A1.2})$$

The last three terms in (A1.2) come from utilizing more bandwidth of group g' , thus results in NOMA sum-rate gain for near UTs in both groups and OMA sum-rate loss for near UTs in group g' . Let the first and second logarithmic terms in (A1.1) be O_f and N_f , respectively, where O stands for OMA, and N means NOMA. Then, (A1.1) can be expressed as

$$\begin{aligned} S_{g,f} & \approx a[(1 - \alpha_g)O_f + (\alpha_g + \beta)N_f + \epsilon_{g'}O_f - \epsilon_{g'}N_f] \\ & = S'_{g,f} + a[\epsilon_{g'}O_f - \epsilon_{g'}N_f]. \end{aligned} \quad (\text{A1.3})$$

In the above equation, $S'_{g,f}$ is substituted based on (3.51). Similarly, by letting the logarithmic terms be O_n , N_n , N'_n , E , and O'_n consecutively, (A1.2) can be simplified as

$$\begin{aligned} S_{g,n} & \approx a[(1 - \beta)O_n + (\alpha_g + \beta)N_n + \epsilon_{g'}(-N_n + N'_n + E - O'_n)] \\ & = S'_{g,n} + a[\epsilon_{g'}E - \epsilon_{g'}O'_n], \end{aligned} \quad (\text{A1.4})$$

where $S'_{g,n}$ is in (3.50). Since the near UTs experience a similar channel condition of each other in the overlapped cluster, it can be assumed that $N_n \approx N'_n$, consequently, (A1.4) is

obtained. By summing $S_{g,f}$ and $S_{g,n}$, the total sum-rate is obtained as

$$\begin{aligned} S_g &\approx S'_{g,f} + a [\epsilon_{g'} O_f - \epsilon_{g'} N_f] + S'_{g,n} + a [\epsilon_{g'} E - \epsilon_{g'} O'_n] \\ &= S'_g + \Delta_s M \epsilon_{g'} [O_f - N_f + E - O'_n], \end{aligned} \tag{A1.5}$$

where $S'_g = S'_{g,f} + S'_{g,n}$. The proof is complete.



Appendix A2 Proof of analytical OP expression

In order to solve the joint probability in the outage probability (3.76), (3.77) and (3.78), the independent probabilities are firstly simplified by substituting the respective SINRs from (3.59) and (3.60) as follows:

$$\begin{aligned}
 \mathbb{P}[\gamma_{k \rightarrow 3,i} \leq \gamma'_k] &= \mathbb{P}\left[\frac{\alpha_k \rho |\hat{h}_{3,i}|^2}{\sum_{k'=k+1}^3 \alpha_{k'} \rho |\hat{h}_{3,i}|^2 + 1} \leq \gamma'_k\right], \\
 &= \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \frac{\gamma'_k}{\rho(\alpha_k - \gamma'_k \sum_{k'=k+1}^3 \alpha_{k'})}\right] \\
 &= \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \Psi_{k \rightarrow 3,i}\right], k \in \{1, 2, 3\}.
 \end{aligned} \tag{A2.6}$$

$$\begin{aligned}
 \mathbb{P}[\gamma_{k \rightarrow 2} \leq \gamma'_k] &= \mathbb{P}\left[\frac{\sum_{i=1}^2 \alpha_k \rho |\hat{h}_{2,i}|^2}{\sum_{i=1}^2 \sum_{k'=k+1}^3 \alpha_{k'} \rho |\hat{h}_{2,i}|^2 + 1} \leq \gamma'_k\right], \\
 &= \mathbb{P}\left[\sum_{i=1}^2 |\hat{h}_{2,i}|^2 \leq \frac{\gamma'_k}{\rho(\alpha_k - \gamma'_k \sum_{k'=k+1}^3 \alpha_{k'})}\right], \\
 &= \mathbb{P}\left[\sum_{i=1}^2 |\hat{h}_{2,i}|^2 \leq \Psi_{k \rightarrow 2}\right], k \in \{1, 2\}.
 \end{aligned} \tag{A2.7}$$

$$\mathbb{P}[\gamma_1 \leq \gamma'_1] = \mathbb{P}\left[\sum_{i=1}^2 |\hat{h}_{1,i}|^2 \leq \frac{\gamma'_1}{\rho(\alpha_1 - \gamma'_1 \sum_{k'=k+1}^3 \alpha_{k'})}\right] = \Psi_1. \tag{A2.8}$$

Then, substituting the probability from (A2.6) in (3.76) results in

$$\begin{aligned}
 P_{3,i} &= \mathbb{P}\left[\max\{\Psi_{1 \rightarrow 3,i}, \Psi_{2 \rightarrow 3,i}\} \leq |\hat{h}_{3,i}|^2 \leq \Psi_{3 \rightarrow 3,i}\right] \\
 &\quad + \mathbb{P}\left[\Psi_{1 \rightarrow 3,i} \leq |\hat{h}_{3,i}|^2 \leq \Psi_{2 \rightarrow 3,i}\right] + \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \Psi_{1 \rightarrow 3,i}\right].
 \end{aligned} \tag{A2.9}$$

Using Cumulative Distribution Function (CDF) property; $\mathbb{P}[X_a \leq X \leq X_b] = \mathbb{P}[X \leq X_b] - \mathbb{P}[X \leq X_a]$, (A2.9) can be simplified as results in

$$\begin{aligned}
 P_{3,i} &= \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \Psi_{3 \rightarrow 3,i}\right] - \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \max\{\Psi_{1 \rightarrow 3,i}, \Psi_{2 \rightarrow 3,i}\}\right] \\
 &\quad + \mathbb{P}\left[|\hat{h}_{3,i}|^2 \leq \Psi_{2 \rightarrow 3,i}\right].
 \end{aligned} \tag{A2.10}$$

Since SINR of decoding U_2 is higher than that of U_1 at U_3 , $\max\{\Psi_{1 \rightarrow 3,i}, \Psi_{2 \rightarrow 3,i}\} = \Psi_{2 \rightarrow 3,i}$. Thus,

$$P_{3,i} = \mathbb{P} \left[|\hat{h}_{3,i}|^2 \leq \Psi_{3 \rightarrow 3,i} \right] = \mathbb{P} \left[|\hat{h}_{3,i}|^2 \leq \Psi_{k \rightarrow 3,i}^* \right]. \quad (\text{A2.11})$$

Similarly, by using CDF property in (A2.7), the OP of U_2 can be proved as follows:

$$\begin{aligned} P_2 &= \mathbb{P} \left[\Psi_{1 \rightarrow 2} \leq \sum_{i=1}^2 |\hat{h}_{2,i}|^2 \leq \Psi_{2 \rightarrow 2} \right] + \mathbb{P} \left[\sum_{i=1}^2 |\hat{h}_{2,i}|^2 \leq \Psi_{1 \rightarrow 2} \right], \\ &= \mathbb{P} \left[\sum_{i=1}^2 |\hat{h}_{2,i}|^2 \leq \Psi_{2 \rightarrow 2} = \Psi_{k \rightarrow 2}^* \right]. \end{aligned} \quad (\text{A2.12})$$

with $\Psi_{k \rightarrow 2}^* = \max\{\Psi_{1 \rightarrow 2}, \Psi_{2 \rightarrow 2}\}$. Since the channel gains of all UTs follow Gamma distributions with the respective means and variances that leads to different shape and scale parameters, the outage probability represents the CDF of a Gamma distribution. The proof is complete.

CURRICULUM VITAE

Name Surname : Nann Win Moe Thet

EDUCATION:

B.Sc. :2014, International Islamic University Malaysia (IIUM),
Engineering, Communication Engineering.

M.Sc. :2017, Istanbul Sehir University, Graduate School of En-
gineering and Natural Sciences, Electronics and Computer
Engineering

PROFESSIONAL EXPERIENCE AND REWARDS:

- 2019, Volunteer in organizing 30th IEEE PIMRC Conference, Istanbul, Turkey
- 2020-2021, Erasmus Grant for Erasmus Traineeship Program
- 2017-2021, TÜBITAK PhD Fellowship
- 2015-2017, TÜBITAK Graduate Scholarship Program for International Students
- 2007-2014, YAYASAN ALBUKHARY (Malaysia) Full Scholarship for foundation program and undergraduate program
- 2014, First Class Honor Student (Ranked 2nd among Bachelor of Communication Engineering graduates in IIUM 30th Convocation)
- 2014, Ranked 7th among Bachelor of Engineering (all departments) graduates in IIUM 30th Convocation

PUBLICATIONS, PRESENTATIONS, AND PATENTS ON THE THESIS:

- N.W.M. Thet and M.K. Ozdemir, "Outage probability analysis of reconfigurable intelligent surface-enabled coordinated multi-points NOMA networks," *Trans. on Veh. Technol.*, May. 2021, Submitted.
- N.W.M. Thet and M.K. Ozdemir, "Partial-beam non-Orthogonal multiple access (PB-NOMA) with fuzzy clustering," *Wireless Commun. Lett.*, vol. 10, no. 6, p.1202-1206, Jun. 2021, doi: 10.1109/LWC.2021.3061779.
- N.W.M. Thet, S. Khan, E. Arvas and M.K. Ozdemir, "Impact of mutual coupling on power-domain non-orthogonal multiple access (NOMA)," *IEEE Access*, vol. 8, p.188401-188414, Oct. 2021, doi: 10.1109/ACCESS.2020.3030110.

- N.W.M. Thet, A. Kachroo and M.K. Ozdemir, “Extended reduced-rank joint estimation of direction of arrival with mutual coupling for coherent signals,” *Trans. Emerg. Telecommun. Technol. (ETT)*, vol. 30, no. 12, p.e3620, Apr. 2019, doi: 10.1002/ett.3620.
- N.W.M. Thet, K.W. Elgammal, H.F. Ates and M.K. Ozdemir, “Low-Complexity Deep Learning-Based Beamforming in MISO Systems,” in *2021 IEEE Conference on Signal Processing and Communications Applications (IEEE-SIU)*, 2021, pp. 1-4.
- N.W.M. Thet and M.K. Ozdemir, “Joint Overlap Ratios and Power Allocation with User Fairness in Partial Non-Orthogonal Multiple Access (P-NOMA),” in *2020 IEEE Conference on Signal Processing and Communications Applications (IEEE-SIU)*, 2020, pp. 1-4, doi: 10.1109/SIU49456.2020.9302255.
- N.W.M. Thet, T. Baykas and M.K. Ozdemir, “Performance Analysis of User Scheduling in Massive MIMO with Fast Moving Users,” in *2019 IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (IEEE PIMRC)*, 2019, pp. 1-6, doi: 10.1109/PIMRC.2019.8904133.
- N.W.M. Thet, A. Kachroo and M.K. Ozdemir, “Reduced-rank Joint Estimation of DOA with Mutual Coupling,” in *2018 IEEE Conference on Signal Processing and Communications Applications (IEEE-SIU)*, 2018, pp. 1-4, doi: 10.1109/SIU.2018.8404592.

OTHER PUBLICATIONS, PRESENTATIONS, AND PATENTS:

- N.W.M. Thet, “Performance Evaluation of Filtered Orthogonal Frequency Division,” Ph.D. dissertation, Dept. Electron. and Comp. Eng, Istanbul Sehir University, Istanbul, Turkey, 2018.

ARRAY PROCESSING AND OPTIMIZATION TECHNIQUES OF BEAMFORMING AND RESOURCE ALLOCATION FOR ENHANCED SPECTRAL EFFICIENCY IN 5G AND BEYOND SYSTEMS

ORIGINALITY REPORT

11%	10%	2%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	arxiv.org Internet Source	1%
2	export.arxiv.org Internet Source	1%
3	researchr.org Internet Source	1%
4	theses.whiterose.ac.uk Internet Source	<1%
5	eprints.soton.ac.uk Internet Source	<1%
6	Submitted to Eastern Mediterranean University Student Paper	<1%
7	hdl.handle.net Internet Source	<1%
8	tel.archives-ouvertes.fr Internet Source	<1%