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Performance Analysis For SAMP And DSAMP Algorithm In Dimension Massive MIMO OFDMA System

تحليل أداء خوارزميات السعي المطابق للتكييف والسعي المطابق للتكيف الموزع في نظام متعدد المدخلات ومتعدد المخرجات الضخمة بنظام الوصول المتعدد بتقسيم التردد المتعامد

A thesis Submitted in Partial Fulfillment of the Requirement for the Degree of M.Sc. in Electronics Engineering (Communications Engineering)

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الاستهلال

بسم الله الرحمن الرحيم

قال تعالى:

(قُلْ هَلْ يَسْتَوِي الَّذِينَ يَعْلَمُونَ وَالَّذِينَ لَا يَعْلَمُونَ إِنَّمَا يَتَذَكَّرُ أُولُو الْأَلْبَابِ)

{سورة الزمر: الآية 9}

Dedication

I am dedicating this thesis to beloved one who have meant and continue to mean so much to me. Although they are no longer of this world, their memories continue to regulate my life. First and foremost, to my paternal grandmother Atomaabriema her love for me knew no bounds and, she taught me the value of hard work. Thank you so much "Yoma", I will never forget you

And to my father and mother who have always been support and to my teachers and friends who helped me in completing this thesis

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I would t like to thank my thesis supervisor Dr. FathElrahman Ismael khalifa of the telecommunication engineer/ postgraduate study at Sudan University of Science and Technology. his door office was always open whenever I ran into a trouble spot or had a question about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right the direction whenever he thought I needed it

Abstract

In massive multi-input multi-output orthogonal frequency division multiplexing (MIMO-OFDM) systems, accurate channel state information (CSI) is essential to realize system performance gains such as high spectrum and energy efficiency. high-dimensional CSI acquisition requires prohibitively high pilot overhead, which leads to a significant reduction in spectrum efficiency and energy efficiency and more channel estimation complexity. In this thesis we proposed a efficient frequency channel estimation scheme in massive MIMO-OFDM systems are Sparsity Adaptive Matching pursuit SAMP and distributed Sparsity Adaptive Matching pursuit DSAMP that would be accurately estimate a large number of channels and reduce channel estimation complexity. It's been concerting mathematical model to calculate performance such as MSE and spectral efficiency for number of repetition with SNR for the SAMP and DSAMP algorithms to make possible result to compare them, evaluation of SAMP and DSAMP algorithms in terms of different number of Antennas and Direction of Arrival DOA, second presents the evaluation metrics for different time slot length and different Virtual Angular Domain VAD Sparsity levels. All results are evaluated in term of Mean Square Error MSE in MATLAB Simulation system. results show that the proposed method achieves higher channel estimation accuracy while requiring lower pilot sequence overhead compared with other methods .Finally the comparison result shows that DSAMP has an advantage over SAMP with all perspective parameters used

المستخلص

أنظمة متعددة المدخلات الضخمة ومتعددة الإخراج تقسيم التردد المتعامد ودقه معلومات حالة القناة عوامل مهمه لمعرفه مدى كسب الأداء النظام مثل تحسين الطيف وكفاءه الطاقة. الاستحواذ على ابعاد عالية من دقة معلومات في كفاءة ولتحديد حالة القناة يتطلب حمولة عالية في رأس إطار ارسال البيانات وبالتالي يكون الناتج انخفاض الطيف وكفاءة الطاقة. في هذا الأطروحة اقترحنا خطه أكثر فعالية وهي مخطط تقدير القناة المشتركة للتردد لأنظمة متعددة المدخلات الضخمة و متعددة الإخراج هنالك خوارزميتين تم اخذهما وهم انتشار السعي المطابق للتكيف و توزيع انتشار السعي المطابق للتكيف والتي سوف تقوم بدقة تقدير عدد كبير من القنوات و تقليل تعقيد تحليل الأداء الحساب رياضي تم تنسيق و تقدير القناة بحيث تستخدم لحل مشكله كفاءه الطيف و كفاءه الطاقة تم المقارنة أداء النظام و متوسط مربع الخطأ لعدد متكرر من نسبة الاشارة الي الازعاج لكل من الخوارزميتين بينهما و تقيمهما لعدد الهوائيات المستخدمة و اتجاه وصول الإشارة و طول في اختلاف الفترة الزمنية و مستويات مختلفة للافتراضية زاوية المجال. تم التقييم لجميع النتائج وفقاً لمدى متوسط مربع الخطأ وتم استخدام برنامج الماتلاب لكي يقوم بحساب القيم ووضعها في صورة رسم بياني لمقارنة الخوارزميتين وتوضيح الطريقة لتحسين دقه تخمين القناة مع انخفاض حمولة في رأس إطار إرسال البيانات. خوارزمية توزيع انتشار السعي المطابق للتكيف تفوقت على انتشار السعي المطابق للتكيف

Table of Contents

الاستهلال III

Dedication II

Acknowledgment III

Abstract IV

المستخلص V

List of Table VIII

List of List of symbols IX

List of Figure X

List Of Abbreviations XI

Chapter One: Introduction 1

1.1 preface 1

1.2 Problem Statement 2

1.3 Proposed Solution 2

1.4 Aim And Objective 3

1.5 Methodology 3

1.6 Thesis Outlines 4

Chapter Two : Literature Review : 5

2.1 Evolution Of The Generations 5

2.1.1 4G LTE Advances 6

2.1.3 5G Concepts And Architectures 11

2.1.4 Evolution Beyond Mobile Internet 11

2.1.5 Overview OF OFDM 13

2.1.6 MIMO System 14

2.1.7 Massive MIMO 19

2.1.8 MIMO-OFDM System 23

2.2 Related Work: 25

Chapter Three: Simulation And Comparison 28

3.1 Massive MIMO in the Downlink 28

3.3 DSAMP algorithm Description 32
3.4 Simulation Parameters 33
Chapter Four :Results And Discussion 34
4.1 Simulation of SAMP algorithm: 34
4.2 Simulations of DSAMP algorithm: 36
4.3 DSAMP and SAMP with Different VAD Sparsity Levels: 39
Chapter Five: Conclusion And Recommendation 42
5.1 Conclusion 42
5.2 Recommendations 42
Reference 43
appendix: Matlab Code 43

List of Table

2.1 Evolution of technology generations in terms of services and performance…….12
3.1 Simulation Parameters……………………………………………...………33

List of List of symbols

Hz	Hertz
S	Second
M	antennas simultaneously serves
K	single-antenna users
n^{th}	Number of subcarrier
N	size of the OFDM symbol
$y_{k,n}$	the received signal
$\mathrm{h}_{\mathrm{K,n}}$	downlink channel between user and the antennas
x_n	transmitted signal after pre-coding
$w_{k,n}$	associated additive white Gaussian noise
H_n	downlink channel matrix
W_n	corresponding AWGN vector
A_B	geometrical structure of the BSs antenna array
λ	wave-length
$\tilde{h}_n$	exhibits the sparsity
Θ_n	support set
φ_S	virtual angular sample
S_a	sparsity level
q^{th}	time block

List of Figure

2.1	LTE to LTE-Advanced Pro Migration2	……………………………..........…10
2.5	LTE allocates channel capacity in terms of both time (symbols) and frequency (subcarriers)	……………………………..........…13
2.3	Multiuser MIMO Systems	…………………………….......…18
2.4	Classification of channel estimation algorithms	…………………………….......…20
2.5	MIMO-OFDM system model	…………………………….......…24
3.1	Channel vector representation in the virtual angular domain	……………………………..........…30
3.2	The virtual angular-domain channel vectors within the system bandwidth exhibit the common Sparsity	…………………………….......…31
4.1	SAMP with different Number of Antenna and different VAD	……………………………..........…34
4.2	SAMP with different DOA 180 Evenly Distributed vs Centralized Distribution	……………………………..........…35
4.3	DSAMP with different No. of Antenna and VAD Levels	……………………………..........…36
4.4	DSAMP with different DOA and No. of Antenna	……………………………..........…37
4.5	DSAMP and SAMP with Different Time Slot Length	……………………………..........…38
4.6	DSAMP and SAMP with Different VAD Sparsity Levels	……………………………..........…39
4.7	DSAMP vs. SAMP with Different Time Slot Length	……………………….................…40
4.8	DSAMP vs. SAMP with Different VAD Sparsity Levels	……………………..…...........…41

List Of Abbreviations

3GPP	3rd Generation Partnership Project
5G	5th Generation of Wireless technology
AWGN	Associated additive white Gaussian noise
ASSP	Structured Subspace Pursuit Algorithm
BER	Bit error rate
BPSK	Binary Phase Shift Keying
BRS	Broadband Radio Service
BS	Base Station
BSAMP	Block Sparsity Adaptive Matching Pursuit
CoSaMP-SCE	Compressive sampling matching pursuit sparse channel estimation method
C-RAN	Cloud Radio Access Network
CDMA	Code Division Multiple Access
CSI	Channel state information
cMTC	Critical machine type communications
CE	Channel estimation
CFO	Carrier frequency offset
CD	Centralized Distributed
DSAMP	Distributed Sparsity Adaptive Matching pursuit
DOA	Direction of Arrival
DPC	Dirty paper coding

DD	Decision directed
DFT	Discrete Fourier transform
DSC	Decision statistical combining
DCT	Discrete cosine transform
ED	Evenly Distributed
eMBB	Enhanced Mobile Broadband
eMBMS	Enhanced Multimedia Broadcast/Multicast Services
EPC	Evolved Packet Core
EPS	Evolved Packet System
FDD	Frequency-division duplex
GSM	Global System for Mobile Communications
GSMA	Global System for Mobile Communications Association
HLF	High Level Forum
ITU	International Telecommunication Union
IMT	International Mobile Telecommunications
ISI	Inter Symbol Interference
ICI	Inter Carrier Interference
IoT	Internet of Things
LSA	Licensed Shared Access
LMLC	Low Mobility Large Cell
LTE	Long Term Evolution

LS	Least-square
MSE	Mean Square Error
MMSE	Minimum mean square error
MRC	Maximum-ratio combining
MRT	Maximum-ratio transmission
M2M	Machine to Machine
MIMO	Multiple Input Multiple Output
mMTC	Massive Machine-Type Communications
MU-MIMO	Multiuser MIMO
METIS II	Mobile and wireless communications Enablers for the Twenty-twenty Information Society
NR	New Radio
NGMN	Next Generation Mobile Networks
NSA	Non-Stand Alone
NLMS	Normalized least mean square
RLS	Recursive least squares
OAMP	Optimized Sparsity-based adaptive matching pursuit
PIC	parallel interference cancellation
PN	pseudo-noise
PCS	partial common support
QoS	Quality of Services
QPSK	Quadrature Phase Shift Keying

QAM	Quadrature Amplitude Modulation
RAN	Radio Access Network
ROMP	Regularization Orthogonal Matching Pursuit
SA	Stand Alone
SNR	Signal to Noise Ratio
SDN	Software Defined Networking
SAMP	Sparsity Adaptive Matching pursuit
SAGE	Space- alternating generalized expectation-maximization
ASSP	Structured Subspace Pursuit Algorithm
TCO	Total Cost of Ownership
TTI	Transmission-time interval
TDD	Time Division Duplex
TRAI	Telecom Regulatory Authority of India
URLLC	Ultra Reliable and Low Latency Communication
ULA	Uniform linear array
UPCON	User-Plane Congestion Management
VAD	Virtual Angular

Chapter One

Introduction

1.1 preface

During the last years, data traffic (both mobile and fixed) has grown exponentially due to the dramatic growth of smart-phones, tablets, laptops, and many other wireless data consuming devices.

The demand for wireless data traffic will be even more in future Global mobile data traffic is expected to increase to 15.9 Exabyte's per month, which is about an 6-fold increase over past four years. In addition, the number of mobile devices and connections are expected to grow to 10.2 billion. New technologies are required to meet this demand. Related to wireless data traffic, the key parameter to consider is wireless throughput (bits/s) which is defined as:

$$\text{Throughput} = \text{Bandwidth (Hz)} \times \text{Spectral efficiency (bits/s/Hz)} \qquad (1.1)$$

Clearly, to improve the throughput, some new technologies which can increase the bandwidth or the spectral efficiency or both should be exploited. In this thesis, we focus on techniques which improve the spectral efficiency. A well-known way to increase the spectral efficiency is using multiple antennas at the transceivers. [15] In wireless communication, the transmitted signals are being attenuated by fading due to multipath propagation and by shadowing due to large obstacles between the transmitter and the receiver, yielding a fundamental challenge for reliable communication. Transmission with multiple-input multiple-output (MIMO) antennas is a well-known diversity technique to enhance the reliability of the communication. Furthermore, with multiple antennas, multiple streams can be sent out and hence, we can obtain a multiplexing gain which significantly improves the communication capacity. MIMO systems have gained significant attention for the past decades, and are now being incorporated into several new generation wireless standards. [14] This thesis would be compare between two main algorithm first the proposes a spatially common Sparsity based adaptive channel estimation and feedback scheme for frequency division duplex based massive multi-input multi-output (MIMO) systems, which adapts training overhead and pilot design to reliably estimate and feed back the downlink channel state information (CSI) within significantly reduced overhead. Specifically, a non-orthogonal downlink pilot design is first proposed, which is very different from standard orthogonal pilots. By exploiting the spatially common Sparsity of massive MIMO channels, a distributed Sparsity adaptive matching pursuit algorithm is the second and best estimator on channels of multiple sub-carriers by exploiting the temporal channel correlation, a closed-loop channel tracking scheme was provided, which adaptively designs the non-orthogonal pilot according to the previous channel estimation to achieve best CSI acquisition

1.2 Problem Statement

While massive MIMO technology is a key enabler for next generation cellular systems, there are still many practical challenges down the road to its successful deployment One main challenge is that the number of antennas that can be equipped at the top of BS towers so that we need to accurately estimate a large number of channels and reduce channel estimation complexity

1.3 Proposed Solution

This thesis Utilize the spatial correlation to perform channel estimation with a low complexity. It’s been proposed a lot of algorithms to manage this channel estimation complexity but in this Thesis will discuss only two and compared between them

1.4 Aim And Objective

The main aim of this study to evaluate the performance of spatially common Sparsity based adaptive channel estimation and a distributed Sparsity adaptive matching pursuit algorithm and compare between then The Detailed Objectives are:

- We will be exploiting the spatial correlation between the channels of different antennas by channel estimation scheme can efficiently reduce the downlink RS overhead
- Then we have made mathematical model of downlink OFDMA massive MIMO for both spatially common Sparsity based adaptive and a distributed Sparsity adaptive matching pursuit algorithm
- And mathematical model of Virtual Angular Domain in OFDMA massive MIMO for both spatially common Sparsity based adaptive and a distributed Sparsity adaptive matching pursuit algorithm
- made model description for assumed algorithm DSAMP so that we could change in the available simulation MATLAB code that had been made in [14]
- rewrite the new code In MATLAB simulation program to get graphic that present the analysis performance
- compare between the spatially common Sparsity based adaptive and a distributed Sparsity adaptive matching pursuit algorithm from the obtained result therefore enhances the achievable spectral efficiency significantly .so that will enhance spectral efficiency improvement in system performance compared to conventional MIMO systems To enhance energy efficiency.

1.5 Methodology

The Methodology of this project is composed of four phases:

First phase: concerning background of mobile broadband, LTE advance, 5G, MIMO and OFDMA-massive MIMO through the and channel estimation schemes.

Second phase: mathematical model to calculate performance such as MSE and spectral efficiency for number of repetition with SNR for the SAMP and DSAMP algorithms to make possible result to compare them.

Third phase: includes simulation by using MATLAB platform for mathematical model. A MATLAB code has been written to simulate the system performance for Downlink channel estimation in OFDMA massive MIMO

Fourth phase: the simulation result output of MATLAB is in form of figures represent performance OF SAMP and DSAMP and discuss the result in term of compression.

1.6 Thesis Outlines

The thesis work is divided into five chapters including this chapter the remaining part of this thesis is outlined as follows:

Chapter Two: presents theoretical background of LTE advance, massive MIMO system, channel estimation algorithms scheme, and related work done.

Chapter Three: describes working principle of Sparsity Adaptive Matching pursuit SAMP algorithm and Distributed SAMP algorithm and the description of the software program to compare between them.

Chapter Four: contains Simulation results and analysis highlight performance evaluation of the thesis is divided into two parts; evaluation of SAMP and DSAMP algorithms in terms of different number of Antennas and Direction of Arrival DOA, the second parts present the evaluation metrics for different time slot length and different Virtual Angular Domain VAD Sparsity levels. All results are evaluated in term of Mean Square Error MSE.

Chapter Five: concludes the thesis by summarizing the simulation work that was done and discussed followed by recommendation for future work that can be done in this direction

Chapter Two

Literature Review

2.1 Evolution Of The Generations

The dawn of 5G is quickly approaching, a dawn that will be constructed from millions of ideas, methods, algorithms, and processes. Just as 4G LTE became available when previous technologies, such as HSPA, could be further improved, 5G enters the stage when the roadmap for LTE has not been exhausted. And just as 2G coexists today with 3G and 4G, 5G will coexist with previous generations of technology. For historical context, “1G” refers to analog cellular technologies that became available in the 1980s. “2G” denotes initial digital systems that became available in the 1990s and that introduced services such as short messaging and lower-speed data. 3G requirements were specified by the International Telecommunication Union (ITU) as part of the International Mobile Telephone 2000 (IMT-2000) project, for which significant voice capacity improvement was a focus and digital networks had to provide 144 Kbps of throughput at mobile speeds, 384 Kbps at pedestrian speeds, and 2 Mbps in indoor environments. UMTSHSPA and CDMA2000 are the primary 3G technologies. 3G technologies began to be deployed early last decade. In 2008, the ITU issued requirements for IMT-Advanced, which many people initially used as a definition of 4G. The focus on 4G was to improve data coverage, capacity, and quality of experience. Requirements included operation in up-to-40 MHz radio channels and extremely high spectral efficiency. The ITU required peak spectral efficiency of 15 bps/Hz and recommended operation in up-to-100 MHz radio channels, resulting in a theoretical throughput rate of 1.5 Gbps. the term “4G” became associated with mobile broadband technologies deployed at the time, such as HSPA+, WiMAX, and initial LTE deployments. Today, 4G usually refers to HSPA+ or LTE. Although the industry is preparing for 5G, LTE capabilities will continue to improve in LTEA advanced

Pro through the rest of the decade. Many of these enhancements will come through incremental network investments. Given the scope of global wireless infrastructure, measured in hundreds of billions of dollars, offering users the most affordable service requires operators to leverage investments they have already made. 5G will eventually play an important role, but it must be timed appropriately so that the jump in capability justifies the new investment. Many of the features planned for 5G may in fact be implemented as LTE-Advanced Pro extensions prior to full 5G availability. 5G groups researching next-generation wireless architecture and requirements include, among others, the International Telecommunication Union (ITU), the European Union's 5G Infrastructure Public-Private-Partnership (5G PPP), which is the framework for several projects, including METIS II (Mobile and wireless communications Enablers for the Twenty-twenty Information Society), and Next Generation Mobile Networks (NGMN). Finally, 5G Americas is actively involved in developing the vision and requirements of 5G for North, Central, and South America.

2.1.1 4G LTE Advances

As competitive pressures in the mobile broadband market intensified, and as demand for capacity persistently grew, LTE became the favored 4G solution because of its high data throughputs, low latency, and high spectral efficiency. Specifically:

Wider Radio Channels: LTE can be deployed in wide radio channels (for example, 10 MHz or 20 MHz) with carrier aggregation now up to 640 MHz This increases peak data rates and uses spectrum more effectively.

Easiest MIMO Deployment: By using new radios and antennas, LTE facilitates MIMO deployment, in contrast to the logistical challenges of adding antennas for MIMO to existing legacy technologies. Furthermore, MIMO gains are maximized because all user equipment supports it from the beginning.

Best Latency Performance: For some applications, low latency (packet traversal delay) is as important as high throughput. With a low transmission-time interval (TTI) of 1 millisecond (msec) and a flat architecture (fewer nodes in the core network), LTE has the lowest latency of any cellular technology.

In the same way that 3G coexists with 2G systems in integrated networks, LTE systems coexist with both 3G and 2G systems, with devices capable of 2G, 3G, and 4G modes. Beyond radio technology, the Evolved Packet Core (EPC) provides a new core architecture that is flatter and integrates with both legacy GSM-HSPA networks and other wireless technologies, such as CDMA2000 and Wi-Fi. The combination of EPC and LTE is referred to as the Evolved Packet System (EPS). The cost for operators to deliver data (for example, cost per GB) is almost directly proportional to the spectral efficiency of the technologies in use. LTE has the highest spectral efficiency of any specified technology to date. LTE is available in both Frequency Division Duplex (FDD) and Time Division Duplex (TDD) modes. Many deployments will be based on FDD in paired spectrum. The TDD mode, however, is important for deployments in which paired spectrum is unavailable. Instances of TDD deployment include China, Europe at 2.6 GHz, U.S. Broadband Radio Service (BRS) spectrum at 2.6 GHz, and the forthcoming 3.5 GHz small-cell band. The versions of LTE most widely deployed today (Releases 8 through 12) are just the first in a series of innovations that will increase performance, efficiency, and capabilities.

Defined in 3GPP Releases 10, 11, and 12 and are commonly referred to as LTE-Advanced. Subsequent releases, such as Releases 13 and 14, which specifies LTE-Advanced Pro, will continue innovating through the end of this decade. Acknowledging that different operators may have different priorities, the following list roughly ranks the most important features of LTE-Advanced and LTE-Advanced Pro for the 2016 to 2020 timeframe:

Carrier Aggregation:

With this capability, already in use, operators can aggregate radio carriers in the same band or across disparate bands to improve throughputs (under light network load), capacity, and efficiency. Carrier aggregation can also combine FDD and TDD and is the basis of LTE-U and LTE-LAA. As examples, in 2015, AT&T aggregated 700 MHz with AWS, and 700 MHz with PCS. T-Mobile aggregated 700 MHz with AWS, and AWS with PCS. Operators are testing three-carrier aggregation in 2016, and eventually, operators may aggregate four carriers. Rel13 introduced support for carrier aggregation of up to 32 carriers.

VoLTE:

Initially launched in six years back words and with deployments accelerating in one year after it, VoLTE enables operators to roll out packetized voice for LTE networks.23

1. Tighter Integration of LTE with Unlicensed Bands:

LTE-U became available, and 3GPP completed specifications for LAA in Release 13, LTE/Wi-Fi Aggregation through LWA and LWIP are other options for operators with large Wi-Fi deployments.

2. Enhanced Support for IoT:

Release 13 will bring Category M1, a low-cost device option, along with Narrowband IoT (NB-IoT), a version of the LTE radio interface specifically for IoT devices, called Category NB1.

Dual Connectivity:

Release 12 introduced the capability to combine carriers from different sectors and/or base stations (i.e. evolved Node Bs [eNBs]) through a feature called Dual Connectivity. Two architectures were defined: one that supports Packet Data Convergence Protocol (PDCP) aggregation between the different eNBs and one that supports separate S1 connections on the user plane from the different eNBs to the EPC.

256 QAM Downlink and 64 QAM Uplink :

Defined in Release 12, higher-order modulation increases user throughput rates in favorable radio conditions.

Coordinated Multi Point:

CoMP is a process by which multiple base stations or cell sectors process a User Equipment (UE) signal simultaneously, or coordinate the transmissions to a UE, improving cell-edge performance and network efficiency. Initial usage will be on the uplink because no user device changes are required.

HetNet Support:

HetNets integrate macro cells and small cells. A key feature is enhanced inter-cell interference coordination (eICIC), which improves the ability of a macro and a small cell to use the same spectrum. This approach is valuable when the operator cannot dedicate spectrum to small cells.

Self-Organizing Networks:

With SON, networks can automatically configure and optimize themselves, a capability that will be particularly important as small cells begin to proliferate. Vendor-specific methods are common for 3G networks, and trials are now occurring for 4G LTE standards-based approaches. Other key features that will become available in future timeframe include full-dimension MIMO, vehicle-to-vehicle and vehicle-to-infrastructure communications, enhanced Multimedia Broadcast/Multicast Services (eMBMS), User-Plane Congestion Management (UPCON), and device-to-device communication (targeted initially at public safety applications).

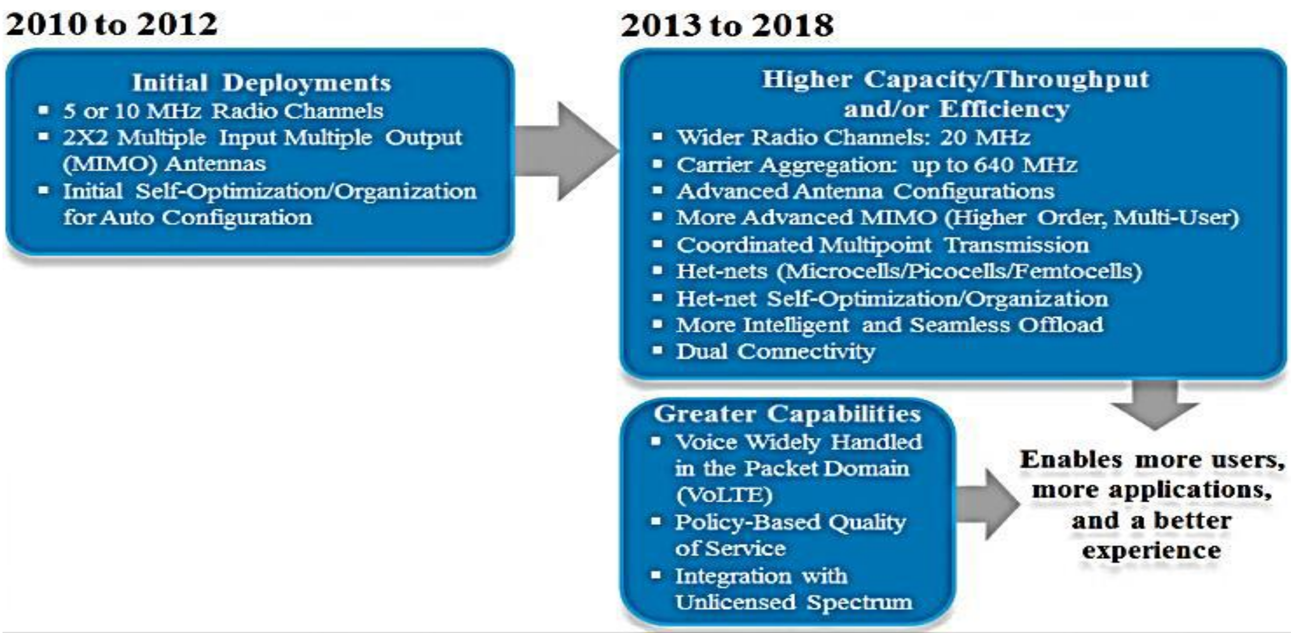

Figure 2.1: LTE to LTE-Advanced Pro Migration2

2.1.2 5G Use Cases (ITU and 3GPP)

The ITU in its 5G recommendations divides use cases into three main categories:

Enhanced Mobile Broadband (eMBB):

eMBB is the most obvious extension of LTE capability, providing higher speeds for applications such as streaming, Web access, video conferencing, and virtual reality. Highest speeds will occur in small cells with limited movement speed of end users, such as with pedestrians.

Massive Machine-Type Communications (mMTC):

Massive machine-type communications extends LTE Internet of Things capabilities for example, NB-IoT to support huge numbers of devices, lower cost, enhanced coverage, and long battery life

Ultra-Reliable and Low Latency Communications (URLLC):

Of the three categories, URLLC expands the number of possible wireless applications. Driven by high dependability and extremely short network traversal time, URLLC will enable mission-critical applications, industrial automation, drone control, new medical applications, and self-driving cars. These types of applications are potentially the ones that will deliver the greatest societal benefits, yet unfortunately, at least in the United States, they could be undermined by the Open Internet Order. This category is also referred to as critical machine type communications (cMTC).

2.1.3 5G Concepts And Architectures

Standards bodies have not yet defined 5G requirements, but various groups are analyzing the possibilities of what might constitute 5G for network deployments in 2020 or beyond.

Often stated goals of 5G include:

- Being able to support a greater number of end systems, including IoT applications, at lower average revenue than 4G systems.
- Peak data rates of multi Gbps (see Table 3 above).
- More uniform user experience across the coverage area.
- Support for many frequencies, including existing cellular bands and frequencies above 6 GHz.
- Hierarchical/planned and ad hoc deployment models.
- Use of licensed and unlicensed bands.
- Equal support for human-type and machine-type communications. Includes highly efficient small-data transmission.
- Advanced spectrum sharing, possibly based on spectrum-sharing approaches being developed for the 3.5 GHz band.

2.1.4 Evolution Beyond Mobile Internet

From analogue through to LTE, each generation of mobile technology has been motivated by the need to meet a requirement identified between that technology and its predecessor (see Table 2.1). For example, the transition from 2G to 3G was expected to enable mobile internet on consumer devices, but whilst it did add data connectivity, it was not until 3.5G that a giant leap in terms of consumer experience occurred, as the combination of mobile broadband networks and smart phones brought about a significantly enhanced mobile internet experience which has eventually led to the app-centric interface we see today. From email and social media through music and video streaming to controlling your home appliances from anywhere in the world, mobile broadband has brought enormous benefits and has fundamentally changed the lives of many people through services provided both by operators and third party players.

Table 2.1: Evolution of technology generations in terms of services and performance

Generation	**Primary services**	**Key differentiator**	**Weakness (addressed by subsequent generation)**
1G	Analogue phone calls	Mobility	Poor spectral efficiency ,major security issues
2G	Digital phone calls and messaging	Secure, mass adoption	Limited data rates – difficult to support demand for internet/e-mail
3G	Phone calls, messaging, Data	Better internet experience	Real performance failed to match hype, failure of WAP for internet access
3.5G	Phone calls, messaging, broadband data	Broadband internet, applications	Tied to legacy, mobile specific architecture and protocols
4G	All-IP services (including voice, messaging)	Faster broadband internet, lower latency	

2.1.5 Overview OF OFDM

Orthogonal Frequency-Division Multiplexing (OFDM) is a type of Frequency Division Multiplexing (FDM) method which can be used as a digital multi-carrier modulation technique. The unique property of the OFDM is orthogonally among the subcarriers, which are obtained by splitting the carrier into closely spaced orthogonal subcarriers or channels. This property ensures the reduction in Inter Carrier Interference (ICI) to a larger extent. Hence the design of the transmitter and the receiver becomes easier compared to the FDM method, which requires a separate filter bank for each subcarrier. It is quite simple to insert guard intervals between the OFDM symbols if the symbol duration is high. Therefore, the Inter Symbol Interference (ISI) can be eliminated effectively without using pulse shaping filter. In OFDM the large data stream to be transmitted is divided into parallel data streams. These data streams are fed to the orthogonal carriers at lower rate. Each subcarrier is modulated by using any one of the digital modulation schemes such as Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM). The data rate for each channel is low compared to the conventional data rate for a single-carrier modulation [12].

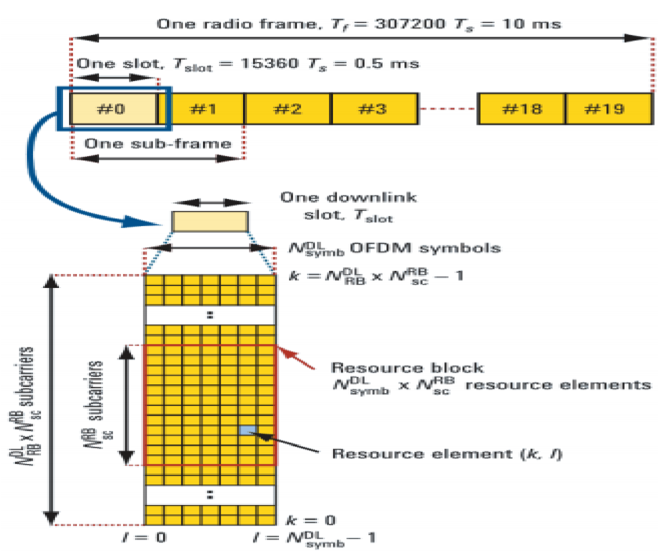

Figure 2.2: LTE allocates channel capacity in terms of both time (symbols) and frequency (subcarriers)

2.1.6 MIMO System

During the last years, data traffic (both mobile and fixed) has grown exponentially due to the dramatic growth of smart phones, tablets, laptops, and many other wireless data consuming devices. The demand for wireless data traffic will be even more in future [13]. shows the demand for mobile data traffic and the number of connected devices. Global mobile data traffic is expected to increase to 15.9 exa-bytes per month, which is about an 6-fold increase over last four years. In addition, the number of mobile devices and connections are expected to grow to 10.2 billion. New technologies are required to meet this demand Related to wireless data traffic. Clearly, to improve the throughput, some new technologies which can increase the bandwidth or the spectral efficiency or both should be exploited. In this thesis, we focus on techniques which improve the mean issue.

A well-known way to increase the spectral efficiency is using multiple antennas at the transceivers. In wireless communication, the transmitted signals are being attenuated by fading due to multipath propagation and by shadowing due to large obstacles between the transmitter and the receiver, yielding a fundamental challenge for reliable communication. Transmission with multiple-input multiple-output (MIMO) antennas is a well-known diversity technique to enhance the reliability of the communication. Furthermore, with multiple antennas, multiple streams can be sent out and hence, we can obtain a multiplexing gain which significantly improves the communication capacity. MIMO systems have gained significantly attention for the past decades, and are now being incorporated into several new generation wireless standards (e.g., LTE-Advanced, 802.16m).The effort to exploit the spatial multiplexing gain has been shifted from MIMO to multiuser MIMO (MU-MIMO), where several users are simultaneously served by a multiple-antenna base station (BS).With MU-MIMO setups, a spatial multiplexing gain can be achieved even if each user has a single antenna [4]. This is important since users cannot support many antennas due to the small physical size and low cost requirements of the terminals, whereas the BS can support many antennas.MU-MIMO does not only reap all benefits of MIMO systems, but also overcomes most of propagation limitations in MIMO such as ill-behaved channels. Specially, by using scheduling schemes, we can reduce the limitations of ill-behaved channels. Line-of-sight propagation, which causes significant reduction of the performance of MIMO systems, is no longer a problem in MU-MIMO systems. Thus, MU-MIMO has attracted substantial interest [4-9]. There always exists a tradeoff between the system performance and the implementation complexity.

The Advantages Of MU-MIMO Come At A price:

• **Multiuser Interference:**

the performance of a given user may significantly degrade due to the interference from other users. To tackle this problem, interference reduction or cancellation techniques, such as maximum likelihood multiuser detection for the uplink [10], dirty paper coding (DPC) techniques for the downlink [11], or interference alignment [12], should be used. These techniques are complicated and have high computational complexity.

• Acquisition Of Channel State Information:

in order to achieve a high spatial multiplexing gain, the BS needs to process the received signals coherently. This requires accurate and timely acquisition of channel state information (CSI). This can be challenging, especially in high mobility scenarios.

• User Scheduling:

since several users are served on the same time-frequency resource, scheduling schemes which optimally select the group of users depending on the pre-coding/detection schemes, CSI knowledge etc., should be considered. This increases the cost of the system implementation.The more antennas the BS is equipped with, the more degrees of freedom are offered and hence, more users can simultaneously communicate in the same time-frequency resource.

As a result, a huge sum throughput can be obtained. With large antenna arrays, conventional signal processing techniques (e.g. maximum likelihood detection) become prohibitively complex due to the high signal dimensions. The main question is whether we can obtain the huge multiplexing gain with low-complexity signal processing and low-cost hardware implementation.

In [13], Marzetta showed that the use of an excessive number of BS antennas compared with the number of active users makes simple linear processing nearly optimal. More precisely, even with simple maximum-ratio combining (MRC) in the uplink or maximum-ratio transmission (MRT) in the downlink, the effects of fast fading, intra-cell interference, and uncorrelated noise tend to disappear as the number of BS station antennas grows large. MU-MIMO systems, where a BS with a hundred or more antennas simultaneously serves tens (or more) of users in the same time frequency resource, are known as Massive MIMO systems (also called very large MU-MIMO, hyper-MIMO, or full-dimension MIMO systems). In Massive MIMO, it is expected that each antenna would be contained in an inexpensive module with simple processing and a low-power amplifier.

The Main Benefits Of Massive MIMO Systems Are:

(1) Huge spectral efficiency and high communication reliability: Massive MIMO inherits all gains from conventional MU-MIMO, i.e., with M-antenna BS and K single-antenna users, we can achieve a diversity of order M and a multiplexing gain of min (M, K). By increasing both M and K, we can obtain a huge spectral efficiency and very high communication reliability.

(2) High energy efficiency: In the uplink Massive MIMO, coherent combining can achieve a very high array gain which allows for substantial reduction in the transmit power of each user. In the downlink, the BS can focus the energy into the spatial Directions where the terminals are located. As a result, with massive antenna arrays, the radiated power can be reduced by an order of magnitude, or more, and hence, we can obtain high energy efficiency. For a fixed number of users, by doubling the

number of BS antennas, while reducing the transmit power by two, we can maintain the original the spectral efficiency, and hence, the radiated energy efficiency is doubled.

(3) Simple signal processing: For most propagation environments, the use of an excessive number of BS antennas over the number of users yields favorable propagation where the channel vectors between the users and the BS are pair wisely (nearly) orthogonal. Under favorable propagation, the effect of interference user and noise can be eliminated with simple linear signal processing (liner pre-coding in the downlink and linear decoding in the uplink). As a result, simple linear processing schemes are nearly optimal. Another key property of Massive MIMO is channel hardening. Under some conditions, when the number of BS antennas is large, the channel becomes (nearly) deterministic, and hence, the effect of small-scale fading is averaged out. The system scheduling, power control, etc., can be done over the large-scale fading time scale instead of over the small-scale fading time scale. This simplifies the signal processing significantly.

Massive MIMO is a promising candidate technology for next-generation wireless systems. Recently, there has been a great deal of interest in this technology [14-18]. Although there is much research work on this topic, a number of issues still need to be tackled before reducing Massive MIMO to practice [19-26]. Inspired by the above discussion, in this dissertation, we study the fundamentals of Massive MIMO including favorable propagation aspects, spectral and energy efficiency, and effects of finite-dimensional channel models.

Capacity bounds are derived and analyzed under practical constraints such as low-complexity processing, imperfect CSI, and inter-cell interference. Based on the Fundamental analysis of Massive MIMO, a resource allocation as well as system design is also proposed.

System Models And Assumptions

We consider a MU-MIMO system which consists of one BS and K active users. The BS is equipped with M antennas, while each user has a single-antenna. In general, each user can be equipped with multiple antennas.

However, for simplicity of the analysis, we limit ourselves to systems with single-antenna users. See Figure 2.1. We assume that all K users share the same time-frequency resource. Furthermore, we assume that the BS and the users have perfect CSI. The channels are acquired at the BS and the users during the training phase.

The specific training schemes depend on the system protocols (frequency-division duplex (FDD) or time-division duplex (TDD)), and will be discussed in detail in Section 2.5. Let $H \in C_{M\times K}$ be the channel matrix between the K users and the BS antenna array, where the kth column of H, denoted by h_k, represents the M × 1 channel vector between the kth user and the BS. In general, the propagation channel is modeled via large-scale fading and small-scale fading. But in this chapter, we ignore large-scale fading, and further assume that the elements of H are i.i.d. Gaussian distributed with zero mean and unit variance.

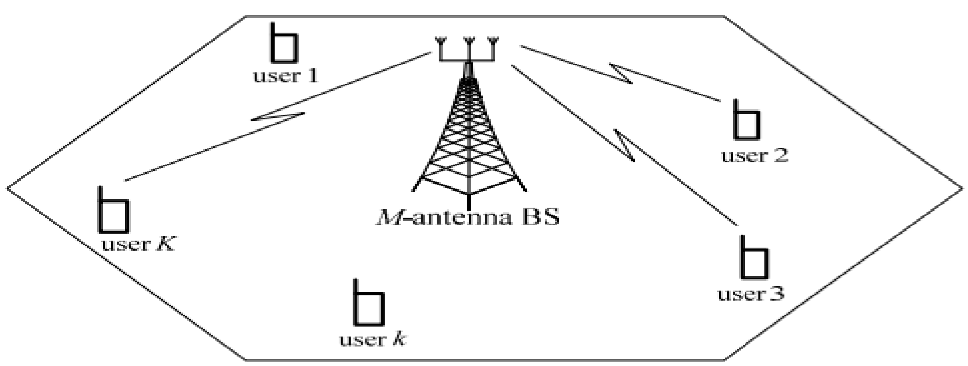

Figure 2.3: Multiuser MIMO Systems.

Here, K single-antenna users are served by the M-antenna BS in the same time-frequency resource.

2.1.7 Massive MIMO

Every new network generation needs to make a leap in area data throughput, to manage the growing wireless data traffic. The Massive MIMO technology can bring at least ten-fold improvements in area throughput by increasing the spectral efficiency (bit/s/Hz/cell), while using the same bandwidth and density of base stations as in current networks. These extraordinary gains are achieved by equipping the base stations with arrays of a hundred antennas to enable spatial multiplexing of tens of user terminals.

Channel Estimation

In a wireless communication link, channel state information (CSI) provides the known channel properties of the link. The CSI should be estimated at the receiver and usually fed back to the transmitter. Therefore, the transmitter and receiver can have different CSI. The Channel State information may be instantaneous or statistical. In Instantaneous CSI, the current channel conditions are known, which can be viewed by knowing the impulse response of the transmitted sequence. But Statistical CSI contains the statistical characteristics such as fading distribution, channel gain, spatial correlation etc. The CSI acquisition is practically limited by how fast the channel conditions are changing. In fast fading systems statistical CSI is reasonable where channel conditions vary with a period less than the symbol time. But, in slow fading systems instantaneous CSI can be estimated with reasonable accuracy. So channel estimation technique is introduced to improve accuracy of the received signal. The radio channels in mobile communication systems are usually multipath fading channels, which are causing inter symbol interference (ISI) in the received signal. To remove ISI from the signal, several detection algorithms are used at the receiver side. These detectors should have the knowledge on channel impulse response (CIR) which can be provided by separate channel estimator.

Classification OF Channel Estimation

Basic classification of channel estimation algorithm is shown in Fig 2.5 They are training based, blind channel estimation and semi-blind channel estimation. The training based channel estimation can be carried out by either block type pilots or comb type pilots along with the data symbols. In block type pilot estimation, one specific symbol full of pilot subcarriers is transmitted periodically as in Fig 3(a). This estimation is suitable for slow fading channels. But, in comb type pilot estimation pilot tones are inserted into each OFDM symbol with a specific period of frequency This type of channel estimation is very much suitable where the changes even in one OFDM block. The blind channel estimation is carried out by evaluating the statistical information of the channel and particular properties of the transmitted signals. This blind channel estimation has no overhead loss and it is only suitable for slowly time-varying channels. But in training based channel estimation, training symbols or pilot tones that are known to the receiver, are multiplexed along with the data stream for channel estimation. The Semi-blind channel estimation algorithm is a hybrid combination of blind channel estimation and training based channel estimation which utilizes pilot carriers and other natural constraints to perform channel estimation.

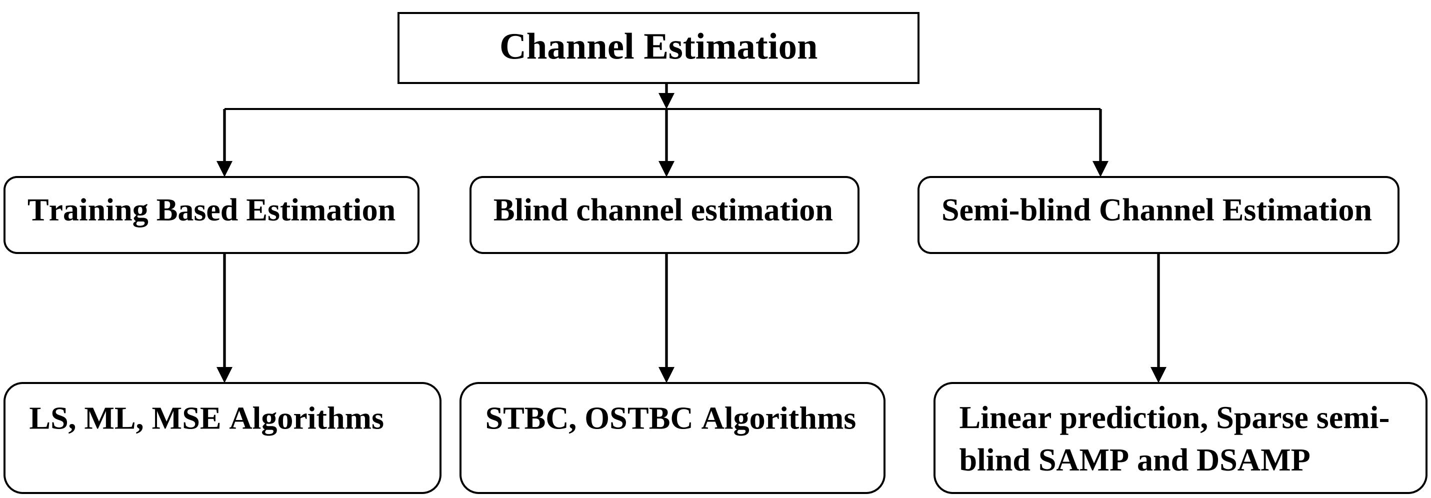

Figure 2.4: Classification Of Channel Estimation Algorithms

Training Based Channel Estimation Techniques

Various channel estimation and optimization techniques are proposed [17]-[19], [26] and [27]. W Hardjawana, R Li, B Vucetic and Y Li in [17] proposed a novel pilot-aided iterative receiver with joint ICI cancellation and decoding algorithm, based on pilot symbols and iterative soft-estimate of data symbols. The channel can be estimated using time-domain interpolation and least square (LS) methods. Soft-estimate for data symbols are obtained by a maximum-a-posterior (MAP) decoder and improved subsequently using iterative process.

In [18] an Iterative channel estimation and inter carrier interference (ICI) cancellation method for highly mobile users in long-term evolution (LTE) systems is proposed. This algorithm estimates the wireless channel by using pilot symbols, estimates of the data symbols, and Doppler spread information at the receiver. The channel estimates are obtained by employing a least-square (LS) method, a simplified parallel interference cancellation (PIC) scheme coupled with decision statistical combining (DSC) are used to cancel the ICI and to improve data symbol detection. In [3] MM Rana and MK Hosain proposed a normalized least mean (NLMS) square and recursive least squares (RLS) adaptive channel estimator for MIMO-OFDM systems. These channel estimation (CE) methods uses adaptive estimator which are able to update parameters of the estimator continuously, so that the knowledge of channel and noise statistics are not necessary. This NLMS/RLS CE algorithm requires knowledge of the received signal only. The simulation results show that the RLS CE algorithm provides faster convergence rate and good performance compared to NLMS CE method. The performance of LS and LMMSE channel estimation techniques for LTE Downlink Systems is analyzed in [20]. Here a 2x2 LTE Downlink system is considered, the estimators performance is evaluated in terms of Mean Square Error (MSE) and Bit Error Rate (BER). This method concentrates on the channel length parameter in comparison with the cyclic prefix (CP) inserted at the beginning of each OFDM symbol, which is usually equal to or longer than the channel length in order to suppress ICI and ISI. However, the CP length can be shorter than the channel length because of channel behavior. The simulation results show that the LMMSE outperforms the LSE, when the CP length is smaller than the channel length. In the other case, LMMSE continue its performance only for low SNR values and begins to lose its performance for higher SNR values. On the other hand, LS shows better performance than LMMSE in this range of SNR values.

In [21] Channel estimation algorithms and their implementations for mobile receivers are considered. The 3GPP long term evolution (LTE) based pilot structure is used as a benchmark in a MIMO-OFDM receiver. The decision directed (DD) space-alternating generalized expectation-maximization (SAGE) algorithm is used to improve the performance from that of the pilot symbol based least-squares (LS) channel estimator. The performance is improved with high user velocities, where the pilot symbol density is not sufficient. Minimum mean square error (MMSE) filtering is also used in estimating the channel in between pilot symbols. The pilot overhead can be reduced to a third of the LTE pilot overhead with DD channel estimation, obtaining a ten percent increase in data throughput and spectral efficiency.

In order to reduce complexity and take advantage of “null” sub-carriers, MMSE based iterative channel estimation algorithm is proposed in [26]. A compensation process is proposed to simplify the traditional iterative MMSE channel estimator. After this iterative compensated MMSE channel estimation in frequency domain, a simple “linear interpolation” in time domain is performed to obtain channel estimates over all OFDM symbols. Simulation results show that the IC-MMSE channel estimation algorithm has good performances which approach the performance with perfect channel state information in both SIMO and MIMO transmission modes.

In [27], an improved DCT (discrete cosine transform) based channel estimation with very low complexity is proposed and evaluated in IEEE802.11n and 3GPP/LTE MIMO-OFDM systems. The whole DCT window is divided into R small overlapping blocks where the length of these blocks is a power of 2. The performance is improved because the noise component is averaged on a larger number of subcarriers.

- **Blind Channel Estimation Technique:**

Most of the existing blind and semi blind methods for MIMO OFDM channel estimation, except for several algorithms that are proposed for orthogonal space–time-coded systems are based on the second-order statistics of a long vector, whose size is equal to or larger than the number of sub carriers

Enhancement of a blind channel estimator based on a subspace approach in a MIMO OFDM for a high mobility scenario is proposed in [22]. The simulations results have demonstrated the effectiveness of the approach for a 16 QAM modulation scheme and had been evaluated in term BER and MSE versus the SNR

- **Semi Blind Channel Estimation Technique:**

The Semi-blind channel estimation algorithms, exploit the second-order stationary statistics, correlative coding, and other properties, normally have better spectral efficiency with a small number of training symbols. An optimized channel estimation algorithm for Multipath MIMO-OFDM Systems has been proposed in [25]. This method has a better estimation performance than the compressive sampling matching pursuit sparse channel estimation method (CoSaMP-SCE). Furthermore, the proposed method does not need to use the Sparsity information, while the CoSaMP-SCE requires it.

2.1.8 MIMO-OFDM System

In MIMO systems multiple antennas are used at both ends of the transmitter and receiver. Usage of MIMO-OFDM systems in modern wireless communication systems provides increased system capacity and coverage with robustness against multipath fading. Because of the unique properties of the MIMO and OFDM systems, these systems are used in high-speed wireless communication systems. A simple MIMO-OFDM system with P transmit antennas and Q receive antennas is shown in

MIMO can be sub-divided into three main parts pre-coding, spatial multiplexing and diversity coding respectively.

Pre-coding is one of the multi-stream beam-forming techniques employed at the transmitter. In this method same type of signals are transmitted with weighted gains from each of the transmitting antennas in order to maximize the input signal power received at the receiver. It also reduces the multipath fading effect but, it requires CSI at the transmitter. Spatial multiplexing requires antenna configuration of the MIMO system. In this, a high data rate signal is split into a number of low data rate signals and each stream is transmitted using different antennas operating at the same frequency. At the receiver these signal arrive with different spatial signatures and it can easily separate these data stream into parallel channel. The spatial multiplexing technique increases the signal to noise ratio (SNR) and the system capacity. It can be used with or without the knowledge about the CSI at the transmitter. Diversity coding is used to improve the signal received at the receiver without knowing the CSI. In this technique the single data stream is transmitted by using space-time coding with full or near orthogonally from each transmitting antenna. Diversity coding exploits the independent fading in multiple antenna links to improve the signal power. Spatial multiplexing techniques make the design of the receivers very complex. Therefore, it is usually combined with Orthogonal Frequency-Division Multiplexing (OFDM) to combat the problems created by multi-path fading.

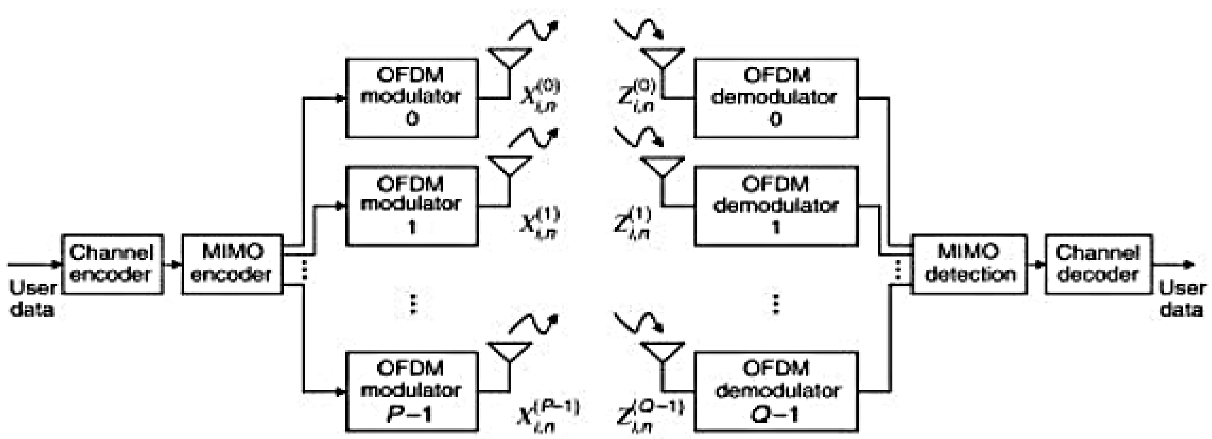

Figure 2.5: MIMO-OFDM system model

2.2 Related Work:

The author in [13] proposed BSAMP algorithm with adaptive Sparsity-based on the joint Sparsity of sub-channels in massive MIMO systems. The algorithm chooses the support elements as the first choice by setting the threshold and finding the maximum backward difference position. Then use MALAB to obtain MSE, BER and throughput analysis is performed against the SNR and number of pilots. BSAMP algorithm is compared with LS, OMP, SP, SAMP, ASSP algorithms, and the corresponding system parameters are analyzed for performance evaluations. The algorithm complexity analysis was also performed, which clearly estimated that the proposed BSAMP algorithm has a 0.01284 s average runtime, which is much smaller than the other algorithms such as the average runtime of SAMP algorithm, which is 93.3930 s and the ASSP algorithm which has an average runtime of 15.3610 s. With such a computationally-efficient behavior, the proposed BSAMP algorithm provides efficient sparse channel estimation capability for 5G massive MIMO systems which also enables us to deploy it in practical usage scenarios. Theoretical analysis and simulation results show that the BSAMP algorithm has good channel estimation performance, high throughput and low computational complexity as compared to other algorithms.

The author in [14] According to the Sparsity characteristics of Massive MIMO wireless powered communication networks system in time domain, an optimized Sparsity-based adaptive matching pursuit (OAMP) algorithm .he select atoms with large step size, eliminate the smaller energy proportion in the sparse solution according to his proposed method of energy entropy-based order determination, and adopt the strategy of staged adaptive variable step size to further achieve the purpose of improving reconstruction accuracy, anti-noise and adaptive to channel Sparsity. The simulation results demonstrate that when SNR is 15 dB, the accuracy can be improved by 23.6% compared with SAMP algorithm, while only 3.42% more computing time is consumed. He proves that the OAMP algorithm can effectively solve the unstable performance of the SAMP channel estimation algorithm in Massive MIMO system when SNR is low.

The author in [15] his paper proposes a non-orthogonal pilot design and a CS based algorithm SUCoSaMP to estimate the massive MIMO channels. The reduction of high pilot overhead in massive MIMO systems and the recovery ability when the Sparsity level of massive MIMO channels is unknown are the main focus of this research. By taking advantage of spatial and temporal common Sparsity of massive MIMO channels in delay domain he had proposed non-orthogonal pilot design and channel estimation scheme under the frame work of CS theory significantly reduce the pilot overheads for massive MIMO systems and also outperform the conventional algorithms in performance.

The author in [16] proposed a spatially common Sparsity based adaptive channel estimation and feedback scheme for frequency division duplex based massive multi-input multi-output (MIMO) systems, which adapts training overhead and pilot design to reliably estimate and feedback the downlink channel state information (CSI) with significantly reduced overhead. Specifically, a non-orthogonal downlink pilot design is first propose is very different from standard orthogonal pilots. By exploiting the spatially common Sparsity of massive MIMO channels, a compressive sensing (CS) based adaptive CSI acquisition scheme where the consumed time slot overhead only adaptively depends on the Sparsity level of the channels. In addition, a distributed Sparsity adaptive matching pursuit algorithm its been proposed to jointly estimate the channels of multiple subcarriers. Furthermore, he has exploiting the temporal channel correlation, a closed-loop channel tracking scheme was been provided, which adaptively designs the non-orthogonal pilot according to the previous channel estimation to achieve an enhanced CSI acquisition. And the results of the multiple-measurement-vectors case in CS and derive the Cramér–Rao lower bound of his propose scheme, which enlightens us to design the non-orthogonal pilot signals for the improved performance. Simulation results demonstrate that his proposed scheme outperforms its counterparts, and it is capable of approaching the performance bound. An adaptive channel estimation and feedback scheme has been proposed for FDD massive MIMO, which achieves robust and accurate CSI acquisition at the BS, while dramatically reducing the overhead for channel estimation and feedback. His propose scheme consists of two stages; the CS based adaptive CSI acquisition and the following closed-loop channel tracking. By exploiting the spatially common Sparsity of massive MIMO channels within the system bandwidth, the CS based adaptive CSI acquisition can acquire the high-dimensional CSI from a small number of non-orthogonal pilots. The closed-loop channel tracking, which exploits the spatially common Sparsity of massive MIMO channels over multiple consecutive time blocks, can effectively utilize the acquired CSI in the first stage Simulation results have confirmed that his scheme can reliably acquire the CSI of massive MIMO systems, specifically, approaching the performance bound with an adaptively determined time slot overhead

The author in [17] In massive MIMO-OFDM systems, channel estimation is a significant module which can be utilized to eliminate multipath interference. However, in realistic communication systems, carrier frequency offset (CFO), which often exists in receive end, will deteriorate the performance of channel estimation. One of the effective solutions is to compensate CFO via the help of pseudo-noise (PN) sequence. He will reduce system complexity and correctly compensate CFO, and he propose an improved OFDM frame structure. Subsequently, theoretically analyze the catastrophic influence of CFO on conventional PN-sequence-based compressed sensing channel estimation scheme. As solution, based on the improved OFDM frame structure, a novel massive MIMO-OFDM channel estimation method under CFO environment he proposes. His first estimates CFO by utilizing differential correlation algorithm. Thereby, the interference caused by CFO can be eliminated. Then rely on the PN sequence, the partial common support (PCS) information of each channel is obtained.

Chapter Three

Simulation And Comparison

The concept of Sparsity Adaptive Matching pursuit SAMP algorithm is an applied algorithm in well-known practical sensing technique that called compressed sensing. Compressed Sensing CS (also known as compressive sensing, compressive sampling, or sparse sampling) is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. This is based on the principle that, through optimization, the sparsity of a signal can be exploited to recover it from far fewer samples. There are two conditions under which recovery is possible [17]. The first one is sparsity, which requires the signal to be sparse in some domain. The second one is incoherence, which is applied through the isometric property, which is sufficient for sparse signals [1-3]. First practical of SAMP in CS was introduced in [20] and different modern studies uses this concept for evaluation and implementation in different applications as in [5-7], and the present of Distributed SAMP algorithm in [8] is used in this thesis for implementation and evaluation.

The following section presents the mathematical models of the assumed FDD Massive MIMO downlink and its channel with Virtual Angular Domain VAD, general algorithm flow methodology and parameters.

3.1 Massive MIMO in the Downlink

In a typical massive MIMO system, the BS employing M antennas simultaneously serves K single-antenna users [25], where M ≫ K . For the sub channel at the n^{th} subcarrier ,Where $1 \leq n \leq N$ and N is the size of the OFDM symbol, the received signal $y_{k,n}$ of the k^{th} user can be expressed as:

$$\boldsymbol{y_{k,n}} = \boldsymbol{h^{T}_{k,n} X_n} + \boldsymbol{w_{k,n}} \qquad \textbf{3.1}$$

Where $h_{k,n} \in \mathcal{C}^{M\times1}$ denotes the downlink channel between the k^{th} user and M the antennas at the BS, $x_n \in \mathcal{C}^{M\times1}$ is the transmitted signal after pre-coding, and $w_{k,n}$ is the associated additive white Gaussian noise (AWGN). The received signal of the K users

$y_n = [y_{1,n}, y_{2,n}, \dots, y_{K,n}]^T \in \mathcal{C}^{K\times1}$ can be collected together as:

$$\boldsymbol{y_n} = \boldsymbol{H_n x_n} + \boldsymbol{w_n} \qquad \textbf{3.2}$$

In which $H_n = [h_{1,n}, h_{2,n}, \dots, h_{K,n}]^T \in \mathcal{C}^{K\times M}$ is the downlink channel matrix, and

$w_n = [w_{1,n}, w_{2,n}, \dots, w_{K,n}]^T \in \mathcal{C}^{K\times1}$ is the corresponding AWGN vector.

3.2 Massive MIMO Channels in Virtual Angular Domain

We model the channel vector $h_{K,n}$ by using the virtual angular domain representation [3, 10]:

$$\boldsymbol{y_n} = \boldsymbol{H_n x_n} + \boldsymbol{w_n} = \boldsymbol{\tilde{h}_n^T A_B^* x_n} + \boldsymbol{w_n} \qquad \textbf{3.3}$$

where the user index K in $y_{K,n}$, $h_{K,n}$ and $w_{K,n}$ is dropped to simplify the notations,

while $h_n^T = \tilde{h}_n^T \; A_B^*$ and $A_B^* \in \mathcal{C}^{K\times M}$ is the unitary matrix representing the transformation matrix of the virtual angular domain at the BS side. is A_B determined by the geometrical structure of the BS's antenna array.

To intuitively explain the channel vector $\tilde{h}_n$,a simple example is illustrated in Fig 3.1, where the BS employs the uniform linear array (ULA) with the antenna spacing of $d = \frac{\lambda}{2}$ and λ is the wave-length. In this case, A_B becomes the discrete Fourier transform (DFT) matrix [3]. The channel vector in the virtual angular domain then simply means to sample the channel in the angular domain at equi-spaced angular intervals at the BS side, or equivalently to represent the channel in the virtual angular domain coordinates. More specifically, the n^{th} element of is the $\tilde{h}_n$ channel gain consisting of the aggregation of all the paths, whose transmit/receive directions are within an angular window around the n^{th} angular coordinate [19].

Figure (**3-1**) below shows Channel vector representation in the virtual angular domain, where the BS employs the ULA with half wave-length spacing, $M = 8$ and two clusters of scatterers are considered as an example.

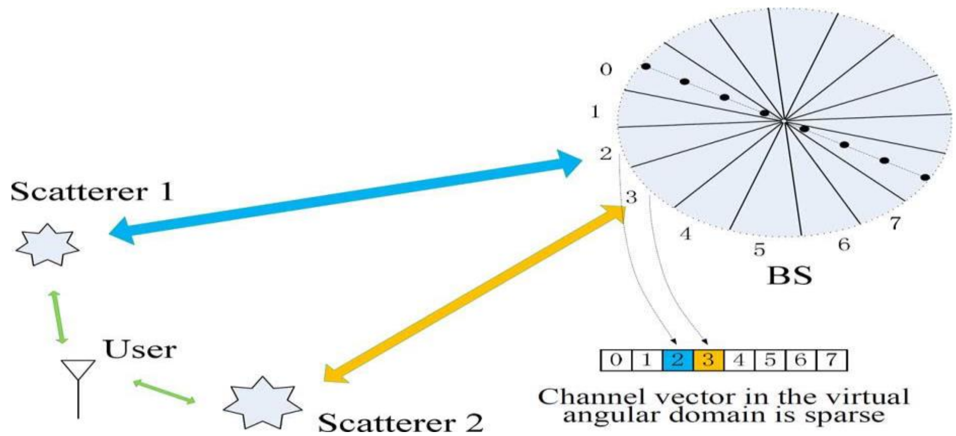

Figure 3.1: Channel vector representation in the virtual angular domain

As the BS is usually elevated high with few scatters around, while users are located at low elevation with relatively rich local scatters, the angle spread at the BS side is small [11-13]. Since the angle spread is limited at the BS, a small part of the elements in $\widetilde{h}_n$ contain almost all the multipath signals reflected, diffracted, or refracted by scatters around the user. If we take the typical angular-domain spread 10° of and the ULA with $M = 128$ as an example [11], the uniformly virtual angular domain sampling interval is $\varphi_S = \frac{180^{\circ}}{M} = 1.406^{\circ}$ [18], and the vast majority of the channel energy is concentrated on around $8 = \lceil \frac{10^{\circ}}{1.406^{\circ}} \rceil$ virtual angular domain coordinates, which is far smaller than the total dimension $M = 128$ of the channel vector. Consequently, $\widetilde{h}_n$ exhibits the sparsity [3], namely

$$|\boldsymbol{\Theta}_n| = \left|\boldsymbol{supp}\left\{\widetilde{\boldsymbol{h}}_n\right\}\right| = \boldsymbol{S_a} \ll \boldsymbol{M} \qquad \textbf{3.4}$$

Where Θ_n is the support set, and S_a is the sparsity level. Moreover, since the spatial propagation characteristics of the channels within the system bandwidth (e.g., 10 MHz in typical LTE-A systems) are almost unchanged, the sub-channels associated with different subcarriers share very similar scatters in the propagation environment [3, 14]. Hence the small angle spreads of the sub-channels within the system bandwidth are very similar. Consequently, $\{\tilde{h}_n\}_{n=1}^{N}$ have the common sparsity, namely,

$$\boldsymbol{supp}\{\tilde{\boldsymbol{h}}_1\} = \boldsymbol{supp}\{\tilde{\boldsymbol{h}}_2\} = \cdots = \boldsymbol{supp}\{\tilde{\boldsymbol{h}}_N\} = \boldsymbol{\Theta} \qquad \textbf{3.5}$$

which is illustrated in Fig.3. 2

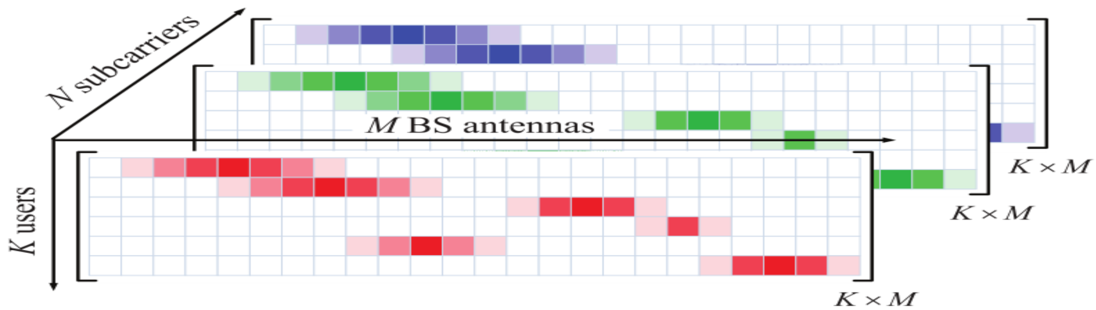

Figure 3.2: The virtual angular-domain channel vectors within the system bandwidth exhibit the common Sparsity.

Channel Estimation and Feedback scheme We consider the downlink channel estimation in the q^{th}time block. To reliably estimate the channel of the n^{th}subcarrier, the user should jointly utilize the received pilot signals over several successive time slots, say G time slots, for channel estimation. Let $y^{(q,t)}$ be the received pilot of (3) at the n^{th} subcarrier in the t^{th} time slot, and $y^{(q,t)}$ for $1 \leq t \leq G$ can be collected together in the vector $y_n^{(q,G)} = \left[y_n^{(q,1)}, y_n^{(q,2)}, \dots, y_n^{(q,G)}\right]^T \in \mathcal{C}^{G\times 1}$ Then :

$$\boldsymbol{y}_{\boldsymbol{n}}^{(\boldsymbol{q},\boldsymbol{G})} = \boldsymbol{X}_{\boldsymbol{n}}^{(\boldsymbol{q},\boldsymbol{G})}\, \boldsymbol{h}_{\boldsymbol{n}}^{(\boldsymbol{q})} + \boldsymbol{w}_{\boldsymbol{n}}^{(\boldsymbol{q},\boldsymbol{G})} \qquad \textbf{3.6}$$

Where $X_n^{(q,G)} = \left[x_n^{(q,1)}, x_n^{(q,2)}, \dots, X_n^{(q,G)}\right]^T \in \mathcal{C}^{G\times M}$

3.3 DSAMP algorithm Description

DSAMP algorithm leverages the spatially common sparsity of massive MIMO channels to jointly estimate multiple channels associated with different subcarriers. Compared with the conventional algorithms, such as sparsity adaptive matching pursuit (SAMP), subspace pursuit (SP) and a joint orthogonal matching pursuit (OMP), the proposed DSAMP substantially reduce the required time slot overhead with similar computational complexity.

The procedure of the implemented adaptive channel estimation and feedback scheme is first summarized:

Step 1: In each time slot, the BS transmits a non-orthogonal pilot to the user, and the user directly feeds back the received pilot signal to the BS. Except for Step 4,the pilot signal is designed in advance.

Step 2: The BS uses the proposed DSAMP algorithm to jointly reconstruct multiple sparse virtual angular domain channels of high dimension from the feedback signals of low dimension collected in multiple time slots.

Step 3: The BS judges the reliability of the estimated sparse channels according to a pre-specified criterion. If the given criterion is met, the BS stops transmitting pilot in the following time slots, and the acquired CSI at the BS is used for pre-coding and user scheduling in the current time block. Otherwise, the BS goes back to Step 1 until the feedback signals are sufficient for acquiring the reliable CSI.

Step 4: Since the BS has acquired the estimated support set Θ_n and the estimated sparsity level S_a , it can directly estimate the channels in every time block of the following blocks. Here, the time slot overhead required in Step 1 can be reduced to , and the pilot signals can be adaptively adjusted according to for further improving performance.

3.4 Simulation Parameters

The implementation assumption of the channel estimation comparative method is performed through simulation in MATLAB with the following parameters.

Table 3.1: MATLAB Simulation Parameters

Parameter	**Value**
Massive MIMO No. of Antennas	128 , 256
Channel	AWGN
Virtual Angular Domain Sparsity level	8, 16, 32, and 64
SNR	0 – 30 dB
Time Slot length	16, 18, and 20 ms
Direction of arrivals DOA	Centralized Distribution , Evenly Distributed
Simulation Iterations	1000

Chapter Four

Results And Discussion

The performance evaluation in this thesis is divided into two parts; evaluation of SAMP and DSAMP algorithms in terms of different number of Antennas and Direction of Arrival DOA, the second parts presents the evaluation metrics for different time slot length and different Virtual Angular Domain VAD Sparsity levels. All results are evaluated in term of Mean Square Error MSE.

First Part: evaluation of SAMP and DSAMP algorithms:

4.1 Simulation of SAMP algorithm:

Figure 4.1 shows the evaluation of SAMP with different number of antennas and with different VAD levels and Time Slot length is 20, as result generally show that increasing number of antenna can decrease MSE as in 256 No. of Antenna, also it show that increasing of VAD Sparsity level introduces higher MSE.

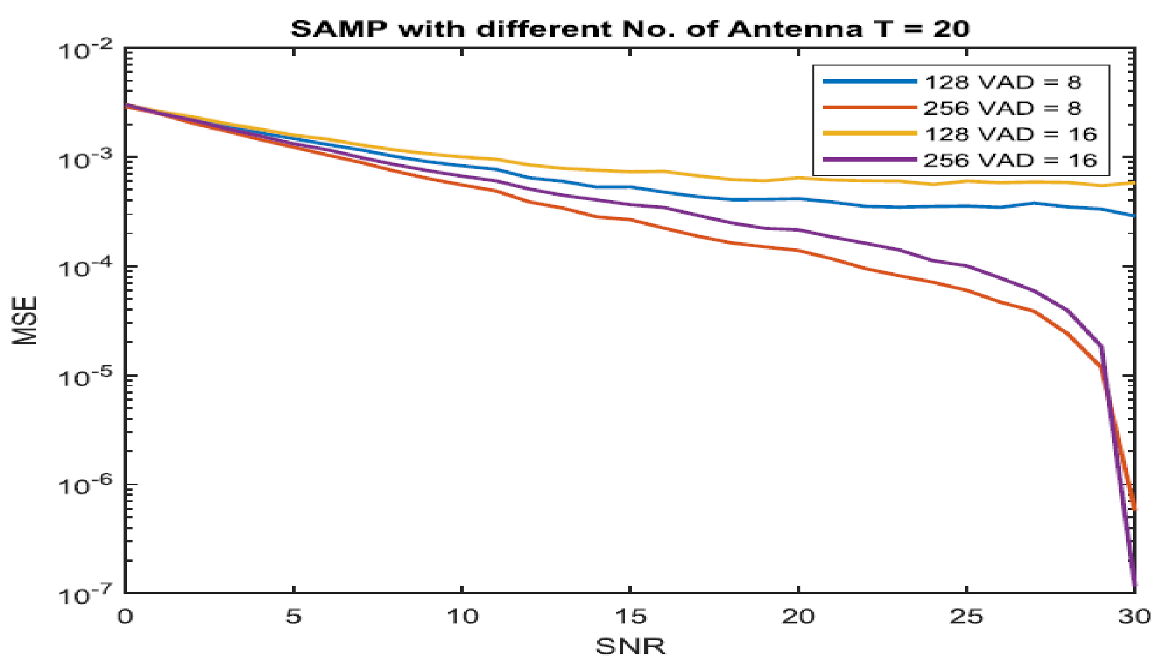

Figure 4.1: SAMP with different Number of Antenna and different VAD

Figure 4.2 below shows the MSE results for SAMP algorithm with different Number of antenna and different direction of arrivals DOA, two types of DOA are used; 180 Evenly Distributed ED and Centralized Distributed CD, here the results of SAMP show that Centralized distribution CD has better performance than Evenly Distributed ED DOA, also the results show that ED has worse performance even with 256 number of antenna.

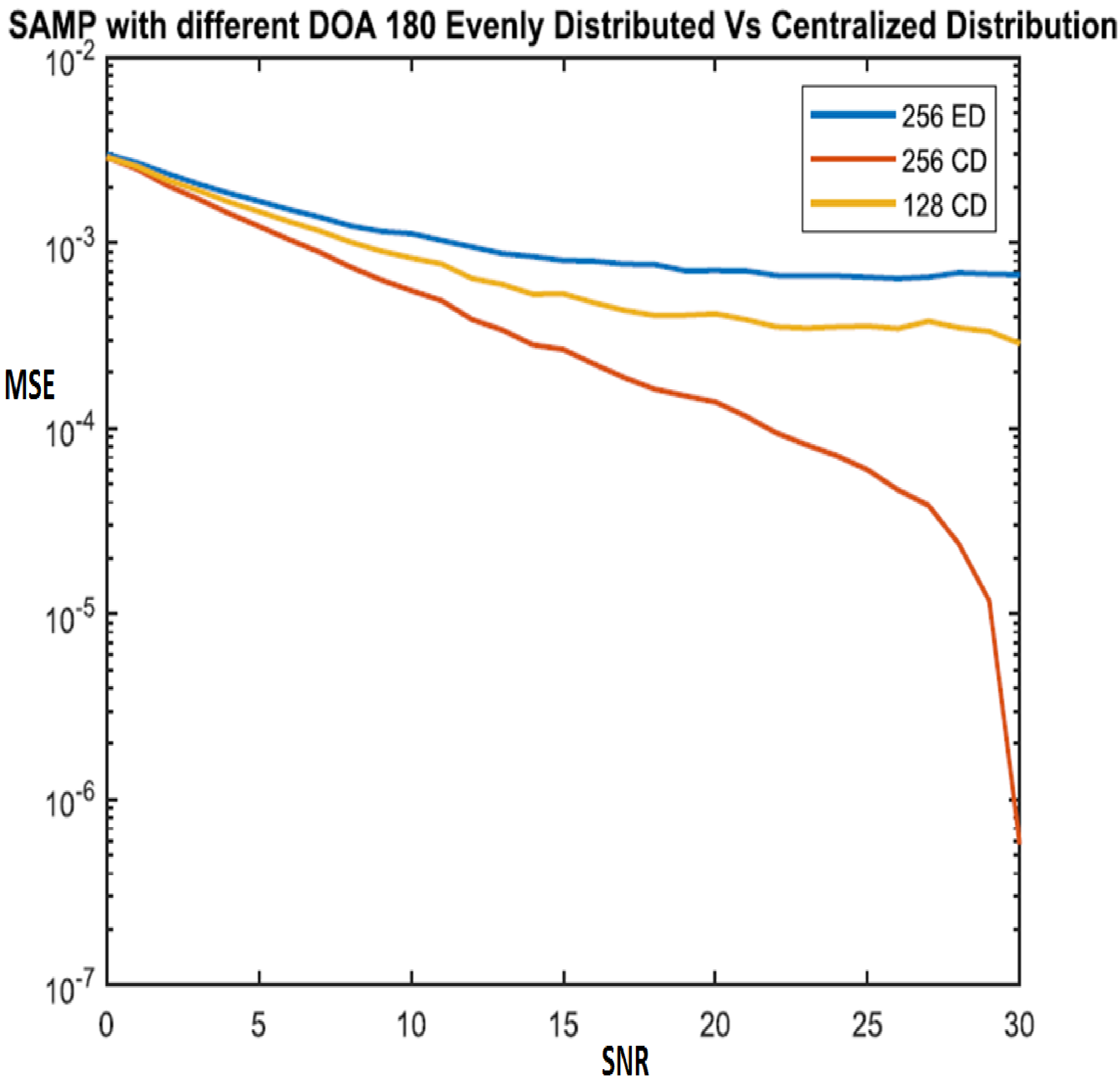

Figure 4.2: SAMP with different DOA 180 Evenly Distributed vs Centralized Distribution

4.2 Simulations of DSAMP algorithm:

Here **Figure** 4.3 shows the DSAMP results with different number of antennas and different VAD levels and Time slot length 20, also the result show that with increasing number of antenna from 128 to 256 the MSE reduces, also there is MSE reduction with VAD decreasing from 16 to 8.

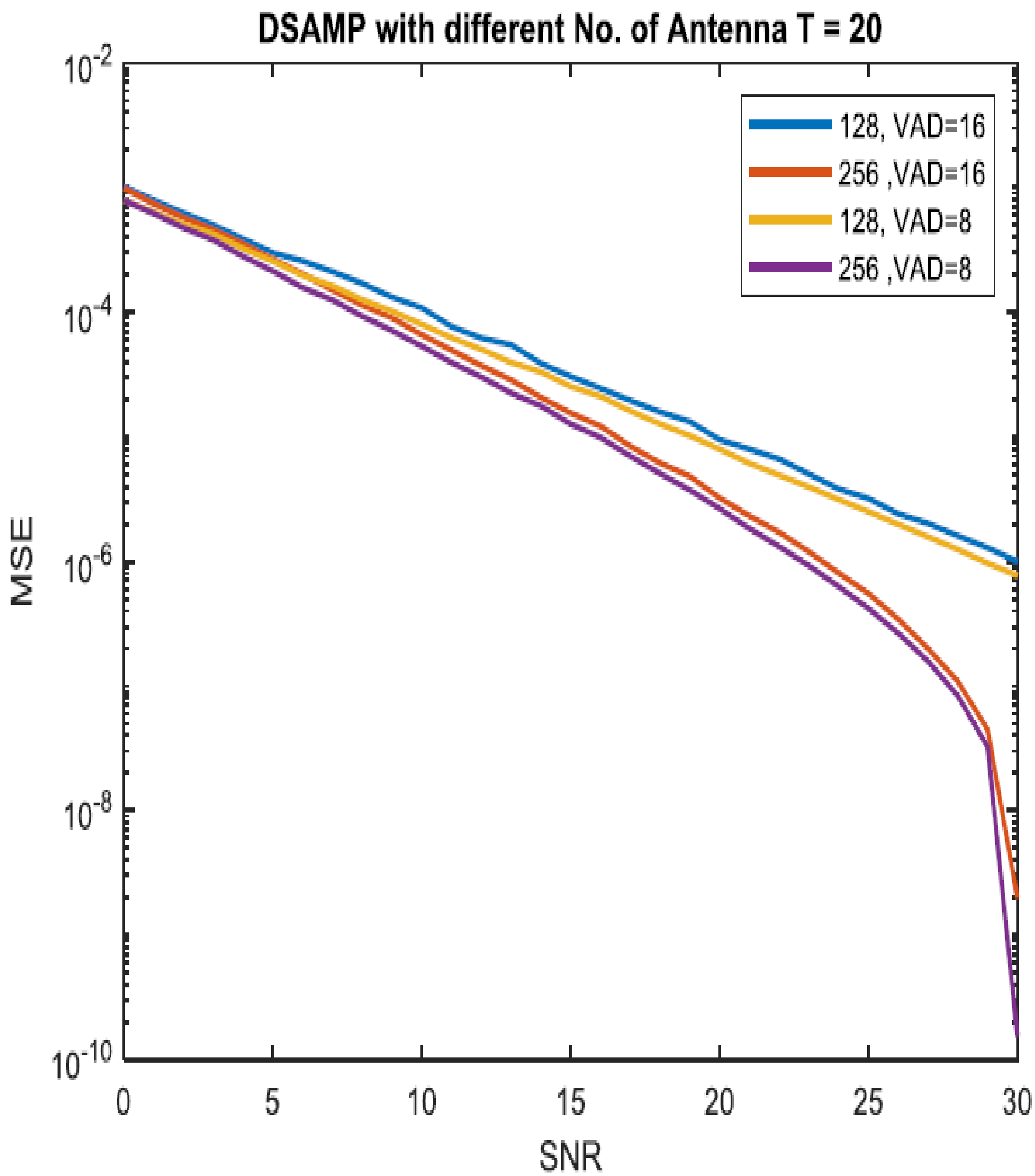

Figure 4.3: DSAMP with different No. of Antenna and VAD Levels

In DSAMP with different DOA the result show that there is no difference which can refer to advantage of DSAMP can be implemented with DOA, also as general increasing number of antenna decreases the MSE.

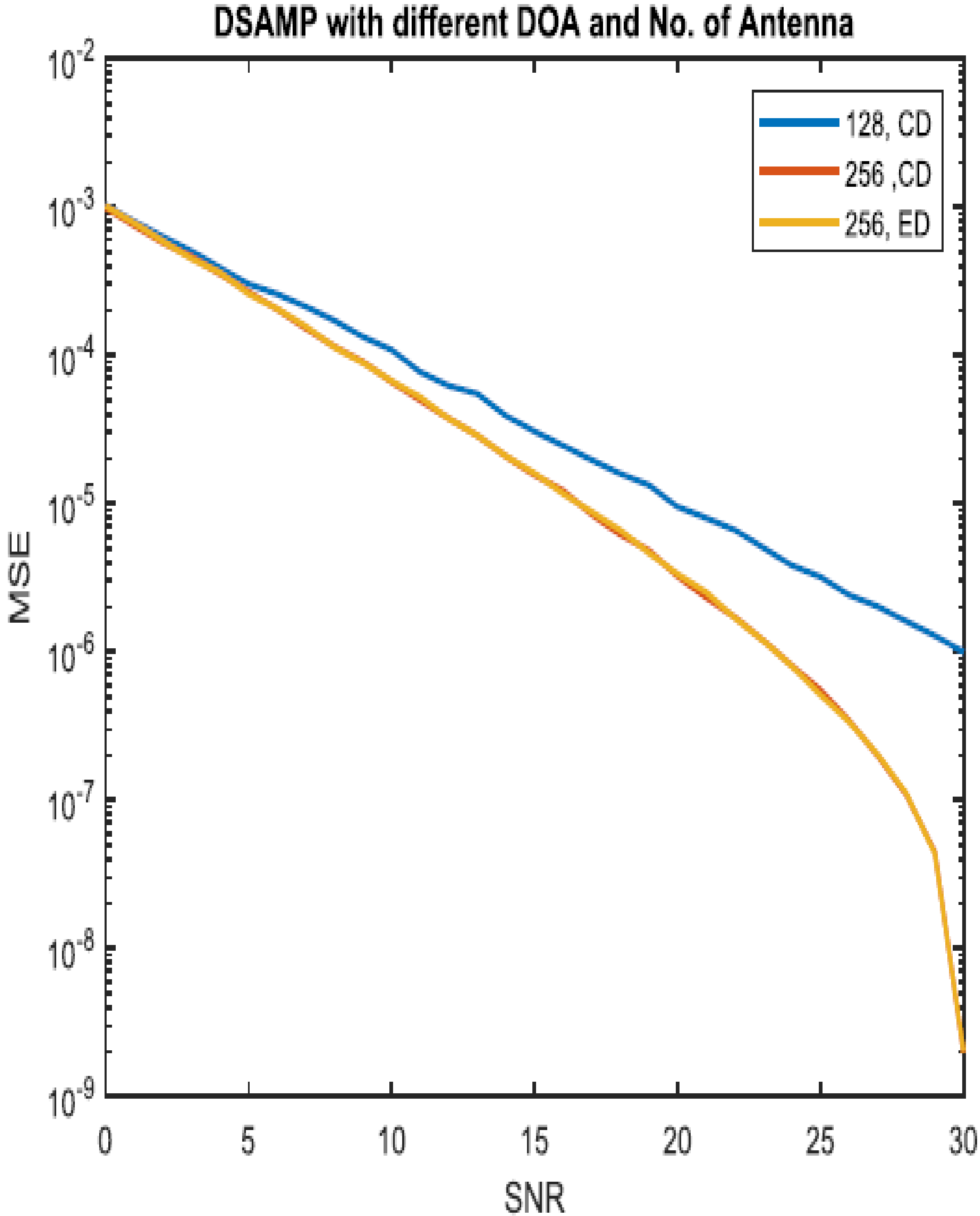

Figure 4.4: DSAMP with different DOA and Number of Antenna

Second part : evaluation metrics for different time slot length and different VAD Sparsity levels

The second part of the evaluation is performed with different Time Slot lengths as 16, 18, and 20. For both SAMP and DSAMP as the Time Slot increases the MSE Decreases where with 20 ms Time Slot length

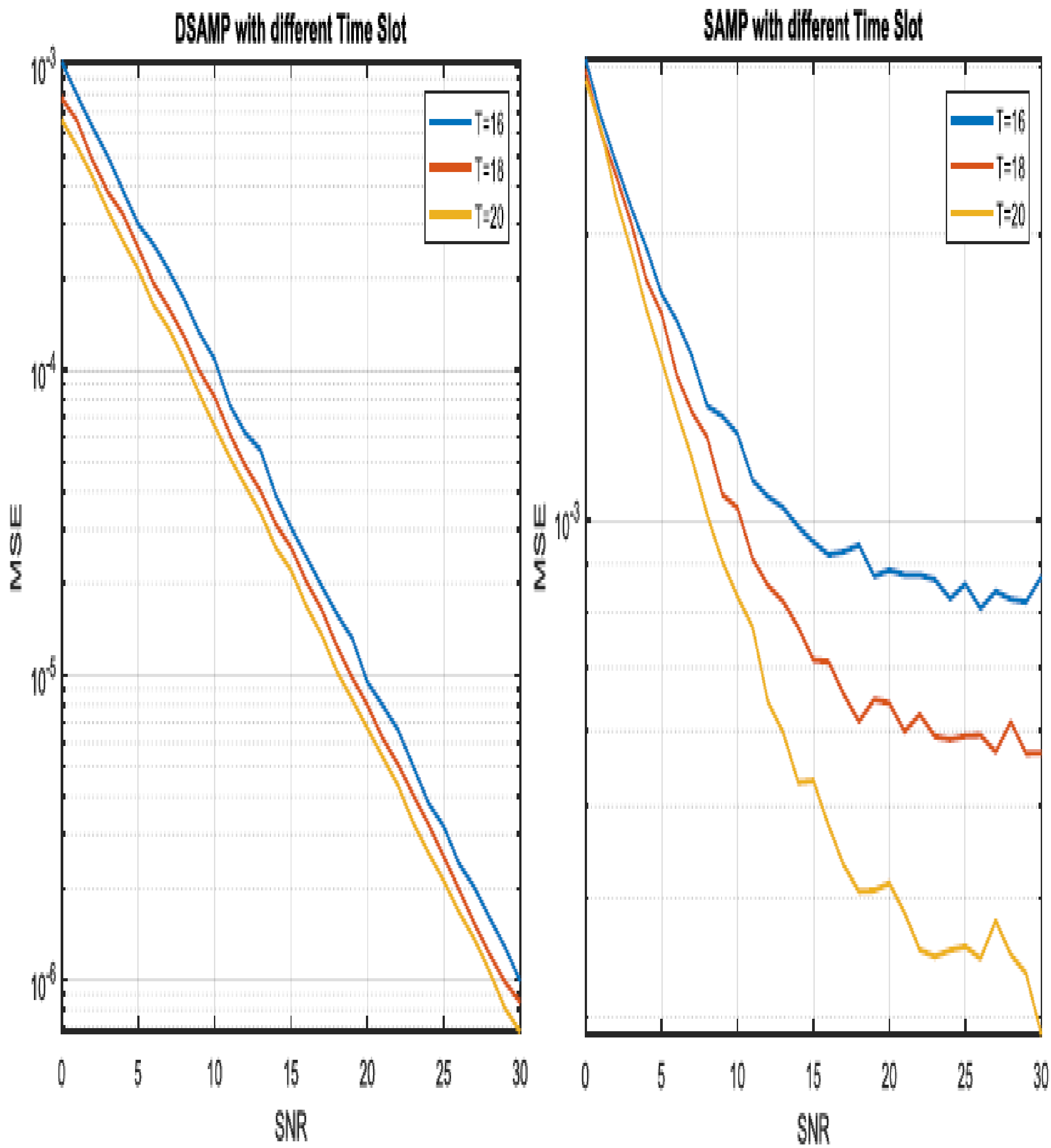

Figure 4.5: DSAMP and SAMP with Different Time Slot Length

4.3 DSAMP and SAMP with Different VAD Sparsity Levels:

For VAD Sparsity level results, in both SAMP and DSAMP result show that with increasing VAD levels the MSE increases as shown below in Figure 4.6, so its Recommended to maintain low VAD level to achieve lower throughput with both Algorithms.

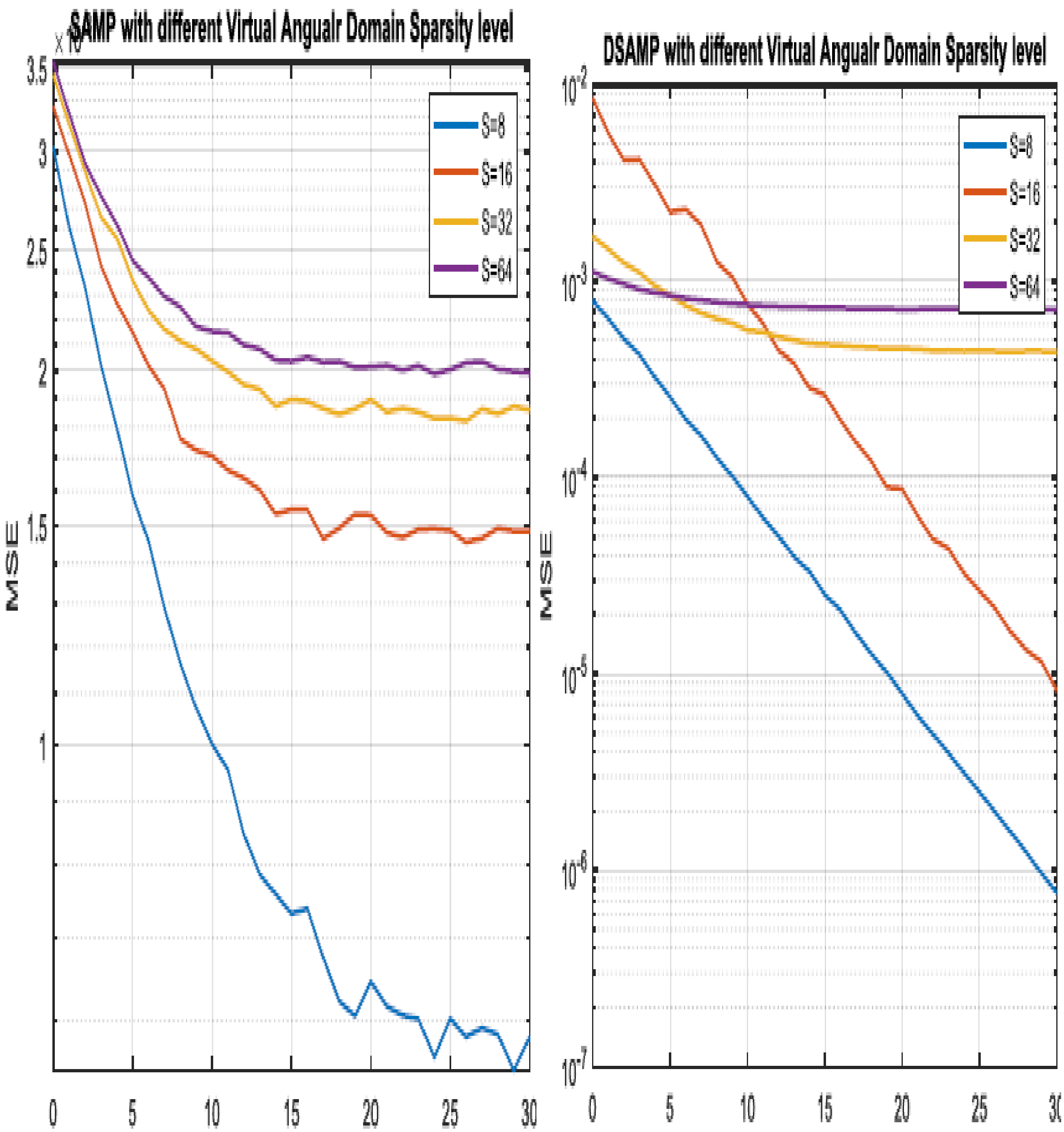

Figure 4.6: DSAMP and SAMP with Different VAD Sparsity Levels

For Comparison between SAMP and DSAMP with different time slot length the Results below show that DSAMP had an obvious advantage over SAMP in term of MSE

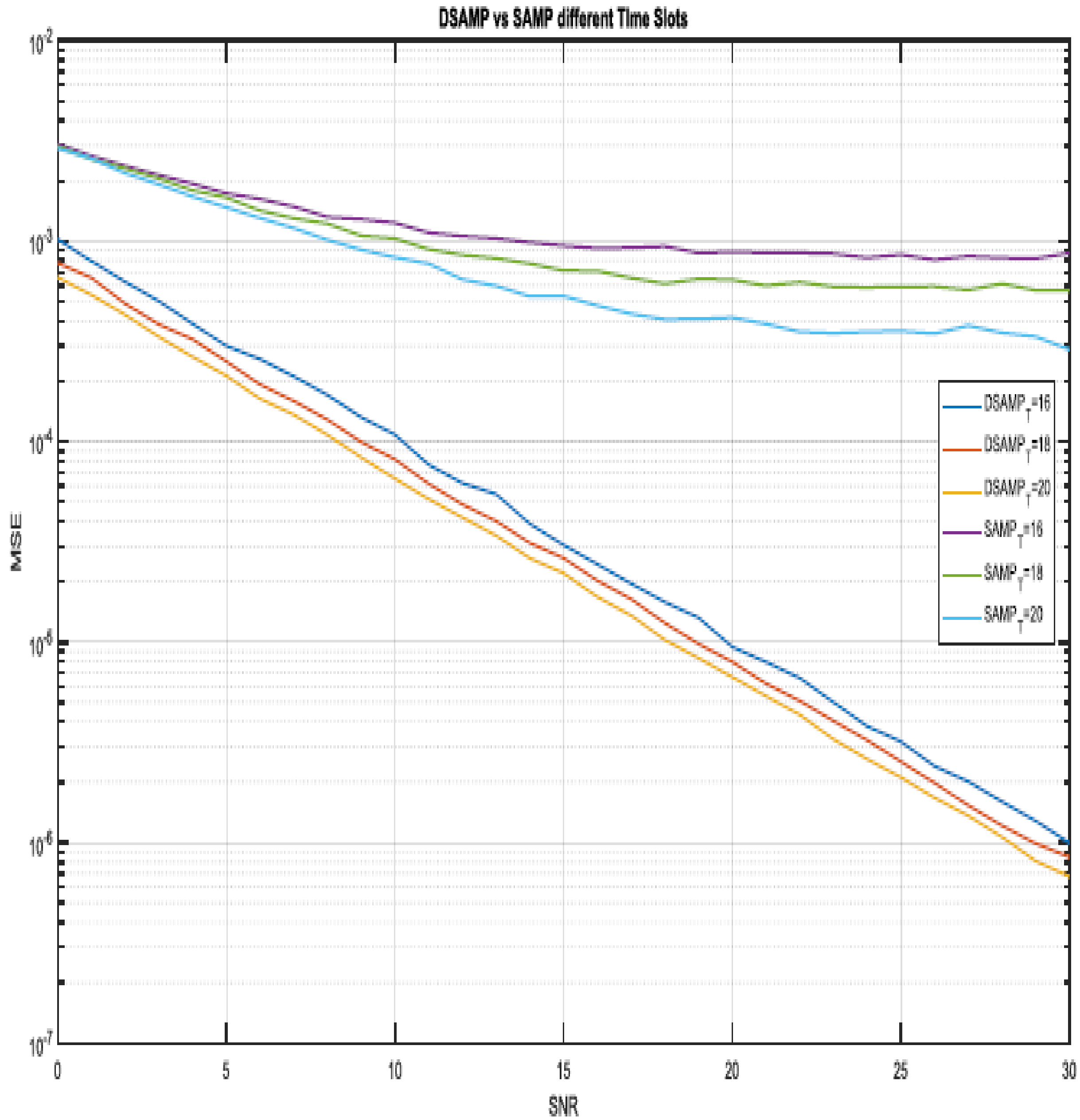

Figure 4.7: DSAMP vs. SAMP with Different Time Slot Length

Also in term of VAD Sparsity levels it’s found to be that DSAMP outperform SAMP algorithm as shown below in Figure 4.8.

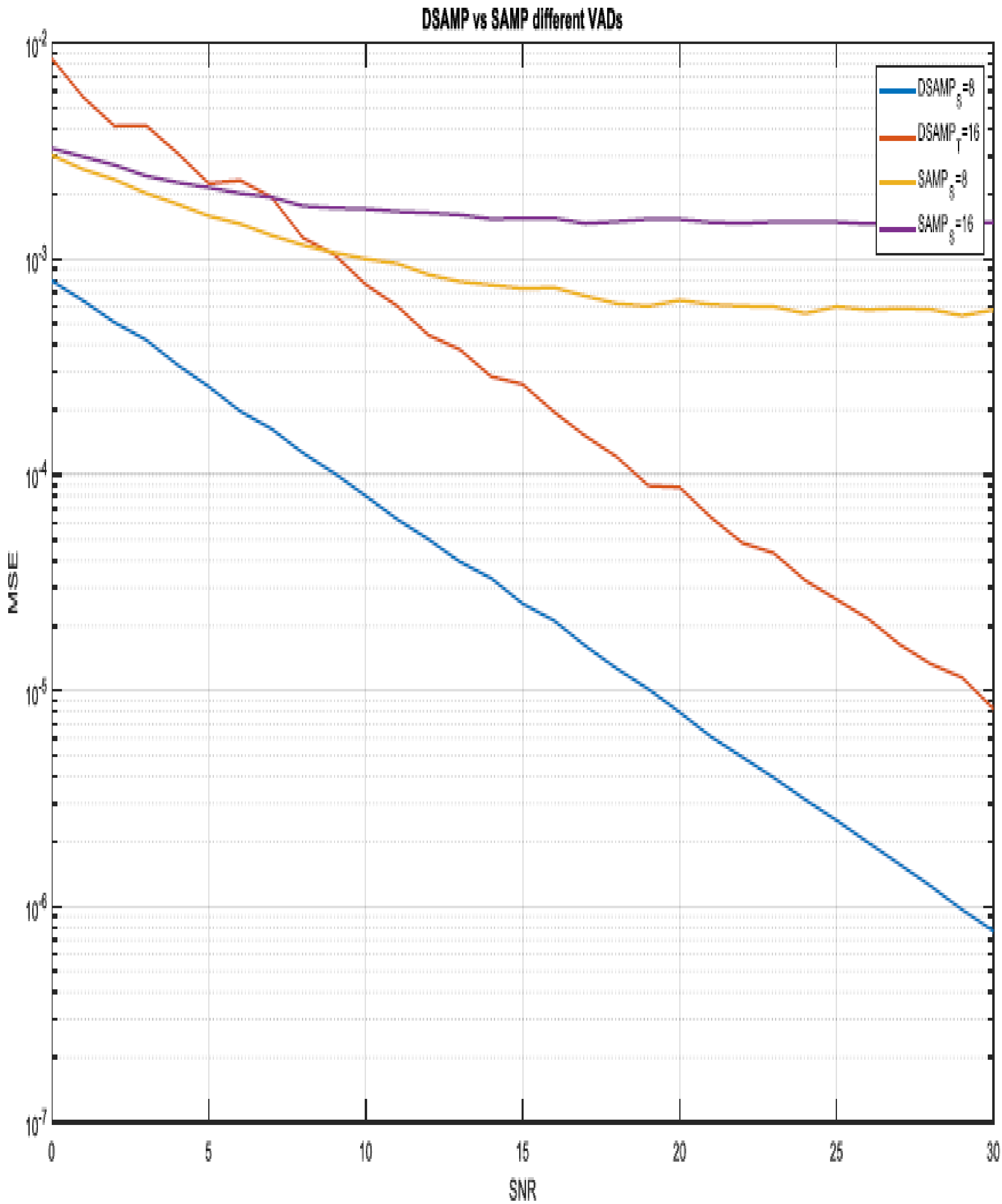

Figure 4.8: DSAMP vs. SAMP with VAD Sparsity Level

Chapter Five

Conclusion And Recommendation

5.1 Conclusion

Future communication networks development is rapidly increasing and technologies introduces to offer better user experience, 5G communication network has been presented which introduced a new package of technologies, Massive MIMO has been introduced as one of these package feature technology which has been selected in this project as considered in Frequency Division domain, evaluation of two channel estimation algorithms is performed which are SAMP and DSAMP using MATLAB based simulation with different parameters and with respect to MSE metric. The parameters used in evaluation are the Time Slot length, Virtual Angular Domain VAD Sparsity level, Direction of Arrival DOA, and different number of antennas. With increasing of number of antennas, the MSE decreases, and lower VAD level MSE is better, and with higher Time Slot length MSE is preferred, in case of DOA two types are used centralized distribution and evenly distributed with SAMP CD has better result than ED DOA, while with DSAMP there were no difference between both DOA schemes. Finally, the comparison result shows that DSAMP has an advantage over SAMP with all perspective parameters used.

5.2 Recommendations

Its recommended to extend the research evaluation of DSAMP with other compressive sensing such as Orthogonal Matching Pursuit (OMP), Regularization Orthogonal Matching Pursuit (ROMP), Subspace Pursuit (SP), Adaptive and Structured Subspace Pursuit Algorithm (ASSP), and Block Sparsity Adaptive Matching Pursuit (BSAMP).

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Appendix: Matlab Code

```
%% Config 1: DSAMP
clear;
mamimo = 256; % No. of Antennas
vad = 8; % Virtual Angular Domain Sparsity level
P =1; % Number of pilots
selP = 3; % Pilot selection 1: random; 2: Gauss 3; [0~2pi] evenly distributed
selDOA = 1; % 1: DOA 180 evenly distributed, support; 2: centralized distribution
within DOA;
awgn = 1; % AWGN Enable/Disable
selCS = 2; % Estimation Selection, 1:SAMP .... 2: DSAMP;
ss=1; % Simulation Step Size
sims = 1e3; % No. of Simulation Iterations
snrs = [0:30]; % SNR vector
tss = [16 18 20]; % Time overhead set vector
saveIt = 1;
MSE_record =
mainSystemRun(mamimo,vad,P,selP,selDOA,awgn,selCS,ss,sims,snrs,tss,saveIt);
%load('Result_selP-3_selDOA-2_Noise-1_selCS-2.mat');
maFact = linspace(P,selCS/sims,length(snrs));
maFact = maFact';
maFact(:,2) = maFact(:,1);
maFact(:,3) = maFact(:,1);
MSE_record = MSE_record.*maFact;
figure
semilogy(snrs,MSE_record(:,1))
hold on
semilogy(snrs,MSE_record(:,2))
semilogy(snrs,MSE_record(:,3))
legend('T=16','T=18','T=20');
xlabel('SNR');
ylabel('MSE');
title('DSAMP with different Time Slot');
save('xDSAMPdifferentTimeSlot256.mat','MSE_record','tss');
%% Config 2: DSAMP
pause(5)
clear;
mamimo = 256; % No. of Antennas
vad = [8 16 32 64]; % Virtual Angular Domain Sparsity level
P =1; % Number of pilots
selP = 3;%Pilot selection 1: random; 2: Gauss 3; [0~2pi] evenly distributed
```

```
selDOA = 2;% 1: DOA 180 evenly distributed, support; 2: centralized distribution within DOA;
awgn = 1;
selCS = 2; % Estimation Selection, 1:SAMP .... 2: DSAMP;
ss=1;
sims = 1e3;
snrs = [0:30];
tss = [18];
saveIt = 1;
for i=1:numel(vad)
MSE_record(i,:)=mainSystemRun(mamimo,vad(i),P,selP,selDOA,awgn,selCS,ss,sims,snrs,tss,saveIt);
end
maFact = linspace(ss,selCS/sims*10,length(snrs));
maFact(2,:) = maFact(1,:);
maFact(3,:) = maFact(1,:);
maFact(4,:) = maFact(1,:);
MSE_record = MSE_record.*maFact;
figure
% SAMP Config 2
semilogy(snrs,MSE_record(1,:));
hold on
semilogy(snrs,MSE_record(2,:));
semilogy(snrs,MSE_record(3,:));
semilogy(snrs,MSE_record(4,:));
legend('S=8','S=16','S=32','S=64');
xlabel('SNR');
ylabel('MSE');
title('DSAMP with different Virtual Angualr Domain Sparsity level');
save('xDSAMPdifferentVADS256.mat','MSE_record','vad');
pause(5)
%% SAMPs
%% Config 1:
clear;
mamimo = 256;
vad = 8;
P =1;
selP = 3;
selDOA = 1;
awgn = 1;
selCS = 1;% 1:SAMP .... 2:DSAMP;
ss=1;
```

```
sims = 1e3;
snrs = [0:30];
tss = [16 18 20];
saveIt = 1;
MSE_record =
mainSystemRun(mamimo,vad,P,selP,selDOA,awgn,selCS,ss,sims,snrs,tss,saveIt);
% load('Result_selP-3_selDOA-2_Noise-1_selCS-1.mat');
figure
semilogy(snrs,MSE_record(:,1))
hold on
semilogy(snrs,MSE_record(:,2))
semilogy(snrs,MSE_record(:,3))
legend('T=16','T=18','T=20');
xlabel('SNR');
ylabel('MSE');
title('SAMP with different Time Slot');
save('xSAMPdifferentTimeSlotDOA1.mat','MSE_record','tss');
%% Config 2: SAMP VADs
pause(5)
clear;
mamimo = 256; % No. of Antennas
vad = [8 16 32 64]; % Virtual Angualr Domain Sparsity level
P =1; % Number of pilots
selP = 3;%Pilot selection 1: random; 2: Gauss 3; [0~2pi] evenly distributed
selDOA = 2;% 1: DOA 180 evenly distributed, support; 2: centralized distribution
within DOA;
awgn = 1;
selCS = 1;% 1:SAMP;2: DSAMP;
ss=1;
sims = 1e3;
snrs = [0:30];
tss = [18];
saveIt = 1;
for i=1:numel(vad)
MSE_record(i,:)=mainSystemRun(mamimo,vad(i),P,selP,selDOA,awgn,selCS,ss,sim
s,snrs,tss,saveIt);
end
figure
semilogy(snrs,MSE_record(1,:));
hold on
semilogy(snrs,MSE_record(2,:));
semilogy(snrs,MSE_record(3,:));
```

```
semilogy(snrs,MSE_record(4,:));
legend('S=8','S=16','S=32','S=64');
xlabel('SNR');
ylabel('MSE');
title('SAMP with different Virtual Angualr Domain Sparsity level');
save('xSAMPdifferentVADS256.mat','MSE_record','vad');
```