ENERGY EFFICIENT DATA DETECTION FOR UPLINK MULTIUSER MASSIVE MIMO SYSTEMS

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MASTER OF TECHNOLOGY

in

ELECTRONICS & COMMUNICATION ENGINEERING

with specialization

COMPUTERS AND COMMUNICATIONS

By

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CERTIFICATE

This is to certify that the project entitled **"ENERGY EFFICIENT DATA DETECTION FOR UPLINK MULTIUSER MASSIVE MIMO SYSTEMS"** is a bona fide record of work done by **Mr. SURLA RAVI TEJA**, Regd. No **16021D3624** under the guidance of **Smt. A. RAJANI** in partial fulfillment of the requirement for **Master of Technology** in **Electronics and Communication Engineering**, with specialization **Computers and Communications** in **University College of Engineering, JNTUK Kakinada** during the academic year 2016 - 2018.

Project Guide	**Head of the Department**
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DECLARATION

I, Mr. S.RAVI TEJA hereby declare that the project report entitled "ENERGY EFFICIENT DATA DETECTION FOR UPLINK MULTIUSER MASSIVE MIMO SYSTEMS" submitted towards the partial fulfillment of the requirements for the award of the degree of MASTER OF TECHNOLOGY in ELECTRONICS AND COMMUNICATION ENGINEERING (ECE) with specialization Computers and Communications, University College of Engineering, JNTUK Kakinada is an authentic record of my own work carried out under the supervision of Smt. A. Rajani, Assistant Professor, Electronics and Communication Department at University College of Engineering, JNTUK Kakinada.

The matter embodied in this dissertation report has not been submitted by me for the award of any other degree. If the information furnished in various chapters is not relevant to the topic and if any mistakes happen to be found in the thesis, I am in a position to give proper explanation and make necessary corrections.

S. RAVI TEJA

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Contents

ABSTRACT

The massive multiuser multiple-input and multiple-output (MIMO) system is widely used in wireless communications considering their reliability and data speed. In multiuser MIMO uplink communications, it is necessary to design linear schemes that can be able to suppress co-channel interferences (CCIs). The optimal and suboptimal data detection algorithms like linear minimum mean square error (LMMSE), coordinate descent method (CDM), etc., may not provide satisfactory bit error rate (BER) performance. Here, we analyze the maximum ratio combining (MRC) receiver for a very large scale multiuser MIMO system under a composite-fading environment. It is developed in the context of an MRC receiver to analyze the mean square error (MSE) parameter with respect to the total training power. Thus with the help of MRC combined with CDM technique, the proposed system results better MSE performance or BER performance.

List of Figures

CHAPTER-1

INTRODUCTION

Now the wireless communications need high quality of services such as high data rate besides it demanding to server more applications and subscribers at a time, this turned as a great challenge especially in cellular communication. MIMO is the advent answer to this challenge. Multiple Input Multiple Output is also known as very large MIMO, Large scale antenna systems, full dimensional MIMO and makes a clean break with current practice through the use of a very large number of service antennas (e.g., hundreds or thousands) that are operated fully coherently and adaptively. For MIMO base stations are equipped with large antenna arrays at transmitter and receiver sides and aimed to serve more independent individual terminals simultaneously under the single frequency-time resource. In MIMO beam forming is exploited by using radio propagation of reciprocity of uplink-downlink. Quality of services that are provided by MIMO depends on the estimation of Channel State Information (CSI) which is obtained from the transmitted uplink pilots by the terminals which makes the MIMO as scalable with respect to the size of base station antennas. In MIMO as antenna arrays size and correspondingly the number of data streams increases the complexity also increases rapidly, every node should be able to aware the data transmitted from one antenna to that transmitted from another, otherwise network performance will be severely affected. When compared to legacy LTE networks MIMO supports higher spectral efficiency and these largest gains obtained from the concept of spatial modulation of several users of cells. So these several gains can only be harvested when there are several users requesting the data at every given millisecond, which requires larger traffic loads than you might think since many seemingly continuous user applications only send data sporadically. Therefore MIMO suffers from the spectral leakage if the traffic load does not meet the required threshold level. In this thesis we propose an optimization technique to optimize the spectral efficiency of MIMO by employing the concept of transmission mode according to the large scale fading loss and spatial correlations. This frame work aimed to optimize spectral efficiency and energy efficiency by considering spatial modulation based schemes such as constellations of space signal, active antennas at base stations and different transmission rates with different transmit diversity gains.

1.1 MIMO (Multiple-input multiple-output)

MIMO stands for multiple input and multiple output. For **MIMO** to **work**, the two wireless stations in communication (i.e., both the access point and the client device) must each have multiple radio/antenna chains that are identical and physically separated from each other by a fixed distance so as to purposely be out of phase at the operational wavelength uses multiple antennas at transmitter and receiver port. An antenna technology that is used both in transmission and receiver equipment for wireless communication MIMO uses multiple antennas to send multiple parallel signals (from transmitter)In an urban environment, these signals will bounce off trees, buildings, etc. and continue on their way to their destination (the receiver) but in different directions. “Multi-path” occurs when the different signals arrive at the receiver at various times. With MIMO, the receiving end uses an algorithm or special signal processing to sort out the multiple signals to produce one signal that has the originally transmitted data. Mathematically, the number of variables exceeds the number of unknowns, so one stream cannot be controlled independently. That last stream, however, can be set to align with another stream, which can be used for multi-stream MIMO clients.

Multiple-input multiple-output (MIMO) systems use multiple antennas at the transmitter and/or receiver to simultaneously transmit different data streams. Multiple antennas provide more degrees of freedom to the propagation channel and improve the throughput and link reliability. Such systems exploit the phenomenon of multipath propagation, which is traditionally a drawback in wireless communications, to the benefit of the user [3]. The improvements in the performance offered by MIMO systems are due to diversity gain, spatial multiplexing gain, array gain and interference reduction [4].

MIMO is a key feature of all the latest broadband systems but the deployment of MIMO on a scale that truly utilizes its potential is yet to be seen because of several reasons. The conventional point-to-point MIMO system can be overcome by using multi-user MIMO systems which use single-antenna terminals that are served simultaneously by an antenna array [5]. Multi-user MIMO systems often employ advanced coding schemes to transmit data simultaneously to many users. However, complex interference mitigation techniques need to be used in the multi-user systems to maintain a controlled level of interuser interference [6].

A widely used suboptimal detection algorithm for uplink multi-user massive MIMO systems is the linear minimum mean square error (LMMSE) algorithm because of its favorable trade-off between bit error rate (BER) performance and complexity. However, the complexity of the LMMSE detector is still considerably high for large-scale MIMO systems.

Several reduced-complexity LMMSE-based detectors have been proposed for uplink massive multi-user MIMO systems to avoid exact large-scale MIMO matrix inversion. So there are various classical iterative algorithms like Richardson method (RM) which have further reduced the complexity of computing matrix inversion [22]. To reduce the computational complexity of data detection, approximate message passing (AMP) and its variants, which were originally designed for compressed sensing, are applied to massive MIMO data detection. The AMP-based detector has the advantage of involving only matrix-vector multiplications rather than matrix-matrix multiplications [25]. However, the AMP algorithm requires knowledge of noise variance and an inappropriate noise variance value would result in severe performance degradation. Moreover, when the MIMO channels are spatially correlated, the AMP-assisted detector may not converge, leadings to unacceptable performance.

The coordinate descent method (CDM), an old and simple technique that is surprisingly efficient and scalable, is now enjoying greatly renewed interest [27]. Its revival is rooted in successful applications to big data optimization, machine learning, and other areas of interest.

Massive MIMO is a novel concept that uses hundreds of antennas at the base station (BS) to serve tens of users simultaneously in the same time-frequency resource. Massive MIMO basically allows us to reap all the benefits of conventional MIMO on a huge scale. In massive MIMO systems, a large number of BS antennas improve spectral efficiency and radiated energy efficiency as compared to the existing wireless technologies. The excessive BS antennas make use of the concept of beamforming by transmitting only in the desired directions so that the radiated energy is focused in a small region and interference is minimized [7]-[8].

Massive MIMO systems allow an increase in theoretical capacity reduction in uplink (UL) and downlink (DL) power consumption. The uplink power can be scaled down by moderately increasing the number of BS antennas [9]. In [10], a peek-to-average-power reduction (PAPR) scheme has been proposed for the downlink of large scale multi-user MIMO systems that enables the use of low cost hardware at the BS. All these reasons make massive MIMO a viable solution for future broadband technologies.

As the number of antennas at the BS increases, linear receivers such as maximum ratio combining (MRC) and minimum mean squared error (MMSE) become optimal. As a result, the acquisition of channel state information (CSI) becomes crucial for the operation of massive MIMO systems [11]-[13]. Acquisition of CSI is done through pilot sequences. Since the pilots require orthogonality between the antennas and all users operate in the same time-frequency resource, such systems have an inherent limitation due to pilot contamination [12]. In [13], it is shown that the main limiting factor in increasing the number of BS antennas is pilot contamination.

With a large number of BS antennas, things that were random before now start to look deterministic. As a consequence, thermal noise and small-scale fading are averaged out in massive MIMO systems. Theoretically, if the number of antennas is allowed to grow without bound, the uncorrelated noise and intracell interference disappear completely [5]. However, the effects of shadowing still remain. Shadowing in wireless systems is known to follow a lognormal distribution. Under Rayleigh fading and lognormal shadowing, the expressions for the probability density function (PDF) of signal-to-interference-plus-noise-ratio (SINR) for massive MIMO systems do not exist in a closed-form. Closed-form expressions for SINR are needed to calculate the outage probability and capacity of the system. However, it is known that a sum or product distribution involving lognormal random variables (RVs) can be well-approximated by a new lognormal RV [14]. The new lognormal RV can then be used to calculate the outage probability and capacity of the system.

In this paper, we analyze the maximum ratio combining (MRC) receiver for a very large scale multi-user MIMO system under a composite-fading environment. It is developed in the context of an MRC receiver to analyze the mean square error (MSE) parameter with respect to the total training power.

1.2 MIMO Applications

- WLAN-WiFi 802.11n
- Mesh networks
- WMAN-WiMAX 802.16e
- 4G
- RFID(Radio frequency Identification)
- Digital home

1.3 Software Tools Required

The implementation will be created within MATLAB, due to its efficiency in dealing with matrices and support for more complex mathematical functions. Version R2017a on Windows will be used for development and testing.

- Operating system : Windows 10.
- Coding Language : MATLAB
- Tool : MATLAB R 2017a

1.4 Thesis Organization

Chapter-2 describes the literature survey. Chapter-3 shows the brief introduction about massive MIMO systems. Chapter-4 explains the system model to be considered for massive MIMO system. Chapter-5 presents the proposed method of energy efficient data detection by designing the receiver antenna. Chapter-6 shows the results obtained by the proposed method and finally concluded this thesis by conclusion.

CHAPTER-2

LITERATURE SURVEY

Most of the previous work on MIMO channels considers small-scale fading only. The Rayleigh-fading channels are chosen to investigate the asymptotic performance of MIMO systems. All of these works focus on the capacity of the system and do not analyze or address the outage probability under the stated channel conditions. Exact lower bounds are used the capacity of linear receivers in massive MIMO systems operating under composite fading environment, but these bounds do not incorporate the PDF of lognormal distribution, instead, the lognormal shadowing is averaged out by performing Monte-Carlo simulations, which limits the analysis of such systems operating under shadowing environments. The authors in some papers incorporate large-scale fading in their system model to derive lower bounds on the SINR for an minimum-mean-squared-error (MMSE) receiver asymptotically, but do not give an exact PDF of SINR for outage calculation. Similarly, the effects of large-scale fading on a zero forcing (ZF) receiver have been analyzed for a finite number of BS antennas but the analysis of MMSE is left out due to its challenging mathematical nature.

A technique proposed by Jung-Chieh Chen et al.[1] presents a major challenge for uplink multiuser massive multiple-input and multiple-output (MIMO) systems is the data detection problem at the receiver due to the substantial increase in the dimensions of MIMO systems. The optimal maximum likelihood detector is impractical for such large wireless systems, because it suffers from exponential complexity in terms of the number of users. Therefore, suboptimal alternatives with reduced complexity, such as the linear minimum mean square error (LMMSE) detector, are necessary. However, the LMMSE detector still introduces high computational complexity, mainly caused by the computation of the Gram matrix and matrix inversion. To reduce the computational complexity of data detection while achieving satisfactory bit error rate (BER) performance, we initially proposed an iterative data detection algorithm that exploits the coordinate descent method (CDM)-based algorithmic framework for uplink multiuser massive MIMO systems. We then developed a reduced-complexity hardware implementation algorithm by leveraging the “one-at-a-time” update property of the CDM-based algorithmic framework. Simulation results revealed that the proposed CDM-based detector provides the same or improved BER performance than the classical LMMSE algorithm at a lower complexity for different test scenarios.

Muhammad Saad Zia et al. [2] considered the uplink of a large-scale multiuser multiple-input-multiple-output (MIMO) system where multiple single antenna terminals transmit simultaneously to an array of hundreds of antennas. The base station (BS) is assumed to have perfect channel state information (CSI). Under Rayleigh fading and lognormal shadowing, the probability density function (PDF) of the received signal-to-interference-plus-noise-ratio (SINR) is approximated by a lognormal distribution for different receiver types and closed-form expressions for the outage probability are presented. The effects of shadowing on the performance of the system are quantified.

D. Gesbert et al. [3] presents an overview of progress in the area of multiple input multiple output (MIMO) space-time coded wireless systems. After some background on the research leading to the discovery of the enormous potential of MIMO wireless links, we highlight the different classes of techniques and algorithms proposed which attempt to realize the various benefits of MIMO including spatial multiplexing and space-time coding schemes. These algorithms are often derived and analyzed under ideal independent fading conditions. We present the state of the art in channel modeling and measurements, leading to a better understanding of actual MIMO gains. Finally, the paper addresses current questions regarding the integration of MIMO links in practical wireless systems and standards.

A. J. Paulraj et al. [4] proposes high data rate wireless communications, nearing 1 Gb/s transmission rates, is of interest in emerging wireless local area networks and home audio/visual networks. Designing very high speed wireless links that offer good quality-of-service and range capability in non-line-of-sight (NLOS) environments constitutes a significant research and engineering challenge. Ignoring fading in NLOS environments, we can, in principle, meet the 1 Gb/s data rate requirement with a single-transmit single-receive antenna wireless system if the product of bandwidth (measured in hertz) and spectral efficiency (measured in bits per second per hertz) is equal to 10/sup 9/. A variety of cost, technology and regulatory constraints make such a brute force solution unattractive, if not impossible. The use of multiple antennas at transmitter and receiver, popularly known as multiple-input multiple-output (MIMO) wireless, is an emerging cost-effective technology that offers substantial leverages in making 1 Gb/s wireless links a reality. The paper provides an overview of MIMO wireless technology covering channel models, performance limits, coding, and transceiver design.

T. L. Marzetta et al.[5] proposes a cellular base station serves multiplicity of single-antenna terminals over the same time-frequency interval. Time-division duplex operation combined with reverse-link pilots enables the base station to estimate the reciprocal forward- and reverse-link channels. The conjugate-transpose of the channel estimates are used as a linear precoder and combiner respectively on the forward and reverse links. Propagation, unknown to both terminals and base station, comprises fast fading, log-normal shadow fading, and geometric attenuation. In the limit of an infinite number of antennas a complete multi-cellular analysis, which accounts for inter-cellular interference and the overhead and errors associated with channel-state information, yields a number of mathematically exact conclusions and points to a desirable direction towards which cellular wireless could evolve. In particular the effects of uncorrelated noise and fast fading vanish, throughput and the number of terminals are independent of the size of the cells, spectral efficiency is independent of bandwidth, and the required transmitted energy per bit vanishes. The only remaining impairment is inter-cellular interference caused by re-use of the pilot sequences in other cells (pilot contamination) which does not vanish with unlimited number of antennas.

F. Rusek et al. [6] proposes that Multiple-input multiple-output (MIMO) technology is maturing and is being incorporated into emerging wireless broadband standards like long-term evolution (LTE) [1]. For example, the LTE standard allows for up to eight antenna ports at the base station. Basically, the more antennas the transmitter/receiver is equipped with, and the more degrees of freedom that the propagation channel can provide, the better the performance in terms of data rate or link reliability. More precisely, on a quasi static channel where a code word spans across only one time and frequency coherence interval, the reliability of a point-to-point MIMO link scales according to Prob(link outage) ` SNR-ntnr where nt and nr are the numbers of transmit and receive antennas, respectively, and signal-to-noise ratio is denoted by SNR. On a channel that varies rapidly as a function of time and frequency, and where circumstances permit coding across many channel coherence intervals, the achievable rate scales as min(nt, nr) log(1 + SNR). The gains in multiuser systems are even more impressive, because such systems offer the possibility to transmit simultaneously to several users and the flexibility to select what users to schedule for reception at any given point in time.

H. Yang et al. [7] proposes Large-Scale Antenna Systems (LSAS) is a form of multi-user MIMO technology in which unprecedented numbers of antennas serve a significantly smaller number of autonomous terminals. We compare the two most prominent linear pre-coders, conjugate beamforming and zero-forcing, with respect to net spectral-efficiency and radiated energy-efficiency in a simplified single-cell scenario where propagation is governed by independent Rayleigh fading, and where channel-state information (CSI) acquisition and data transmission are both performed during a short coherence interval. An effective-noise analysis of the pre-coded forward channel yields explicit lower bounds on net capacity which account for CSI acquisition overhead and errors as well as the sub-optimality of the pre-coders. In turn the bounds generate trade-off curves between radiated energy-efficiency and net spectral-efficiency. For high spectral-efficiency and low energy-efficiency zero-forcing outperforms conjugate beamforming, while at low spectral-efficiency and high energy-efficiency the opposite holds. Surprisingly, in an optimized system, the total LSAS-critical computational burden of conjugate beamforming may be greater than that of zero-forcing. Conjugate beamforming may still be preferable to zero-forcing because of its greater robustness, and because conjugate beamforming lends itself to a de-centralized architecture and de-centralized signal processing.

E.Larsson et al. [8] presents an overview of the massive MIMO concept and contemporary research on the topic. Multi-user MIMO offers big advantages over conventional point-to-point MIMO: it works with cheap single-antenna terminals, a rich scattering environment is not required, and resource allocation is simplified because every active terminal utilizes all of the time-frequency bins. However, multi-user MIMO, as originally envisioned, with roughly equal numbers of service antennas and terminals and frequency-division duplex operation, is not a scalable technology. Massive MIMO (also known as large-scale antenna systems, very large MIMO, hyper MIMO, full-dimension MIMO, and ARGOS) makes a clean break with current practice through the use of a large excess of service antennas over active terminals and time-division duplex operation. Extra antennas help by focusing energy into ever smaller regions of space to bring huge improvements in throughput and radiated energy efficiency. Other benefits of massive MIMO include extensive use of inexpensive low-power components, reduced latency, simplification of the MAC layer, and robustness against intentional jamming. The anticipated throughput depends on the propagation environment providing asymptotically orthogonal channels to the terminals, but so far experiments have not disclosed any limitations in this regard. While massive MIMO renders many traditional research problems irrelevant, it uncovers entirely new problems that urgently need attention: the challenge of making many low-cost low-precision components that work effectively together, acquisition and synchronization for newly joined terminals, the exploitation of extra degrees of freedom provided by the excess of service antennas, reducing internal power consumption to achieve total energy efficiency reductions, and finding new deployment scenarios.

H. Q. Ngo et al. [9] proposes that the use of moderately large antenna arrays can improve the spectral and energy efficiency with orders of magnitude compared to a single-antenna system. A multiplicity of autonomous terminals simultaneously transmits data streams to a compact array of antennas. The array uses imperfect channel-state information derived from transmitted pilots to extract the individual data streams. The power radiated by the terminals can be made inversely proportional to the square-root of the number of base station antennas with no reduction in performance. In contrast if perfect channel-state information were available the power could be made inversely proportional to the number of antennas. Lower capacity bounds for maximum-ratio combining (MRC), zero-forcing (ZF) and minimum mean-square error (MMSE) detection are derived. An MRC receiver normally performs worse than ZF and MMSE. However as power levels are reduced, the cross-talk introduced by the inferior maximum-ratio receiver eventually falls below the noise level and this simple receiver becomes a viable option. The tradeoff between the energy efficiency (as measured in bits/J) and spectral efficiency (as measured in bits/channel use/terminal) is quantified for a channel model that includes small-scale fading but not large-scale fading.

C. Studer et al. [10] investigates an orthogonal frequency-division multiplexing (OFDM)-based downlink transmission scheme for large-scale multi-user (MU) multiple-input multiple-output (MIMO) wireless systems. The use of OFDM causes a high peak-to-average (power) ratio (PAR), which necessitates expensive and power-inefficient radio-frequency (RF) components at the base station. In this paper, we present a novel downlink transmission scheme, which exploits the massive degrees-of-freedom available in large-scale MU-MIMO-OFDM systems to achieve low PAR. Specifically, we propose to jointly perform MU precoding, OFDM modulation, and PAR reduction by solving a convex optimization problem. We develop a corresponding fast iterative truncation algorithm (FITRA) and show numerical results to demonstrate tremendous PAR-reduction capabilities. The significantly reduced linearity requirements eventually enable the use of low-cost RF components for the large-scale MU-MIMO-OFDM downlink.

J. Hoydis et al. [11] considers the uplink (UL) and downlink (DL) of non-cooperative multi-cellular time-division duplexing (TDD) systems, assuming that the number N of antennas per base station (BS) and the number K of user terminals (UTs) per cell are large. Our system model accounts for channel estimation, pilot contamination, and an arbitrary path loss and antenna correlation for each link. We derive approximations of achievable rates with several linear precoders and detectors which are proven to be asymptotically tight, but accurate for realistic system dimensions, as shown by simulations. It is known from previous work assuming uncorrelated channels, that as $N\rightarrow\infty$ while K is fixed, the system performance is limited by pilot contamination, the simplest precoders/detectors, i.e., eigenbeamforming (BF) and matched filter (MF), are optimal, and the transmit power can be made arbitrarily small. We analyze to which extent these conclusions hold in the more realistic setting where N is not extremely large compared to K. In particular, we derive how many antennas per UT are needed to achieve η% of the ultimate performance limit with infinitely many antennas and how many more antennas are needed with MF and BF to achieve the performance of minimum mean-square error (MMSE) detection and regularized zero-forcing (RZF), respectively.

N. Krishnan et al.[12] presents base stations with a large number of transmit antennas can potentially serve a large number of users at high rates. However, the receiver processing in the uplink relies on channel estimates, which are known to suffer from pilot interference. In this paper, making use of the similarity of the uplink received signal in CDMA with that of a multi-cell multi-antenna system, we perform a large system analysis when the receiver employs an MMSE filter with a pilot contaminated estimate. We assume a Rayleigh fading channel with different received powers from users. We find the asymptotic signal to interference plus noise ratio (SINR) as the number of antennas and number of users per base station grow larger while maintaining a fixed ratio. Through the SINR expression we explore the scenario where the numbers of users being served are comparable to the number of antennas at the base station. The SINR explicitly captures the effect of pilot contamination and is found to be the same as that employing a matched filter with a pilot contaminated estimate. We also find the exact expression for the interference suppression obtained using an MMSE filter, which is an important factor when there are a significant number of users in the system as compared to the number of antennas. In a typical set up, in terms of the five percentile SINR, the MMSE filter is shown to provide significant gains over matched filtering and is within 5 dB of MMSE filter with perfect channel estimate. Simulation results for achievable rates are close to large system limits for even a 10-antenna base station with 3 or more users per cell.

J. Jose et al [13] considers a multi-cell multiple antenna system with precoding used at the base stations for downlink transmission. Channel state information (CSI) is essential for precoding at the base stations. An effective technique for obtaining this CSI is time-division duplex (TDD) operation where uplink training in conjunction with reciprocity simultaneously provides the base stations with downlink as well as uplink channel estimates. This paper mathematically characterizes the impact that uplink training has on the performance of such multi-cell multiple antenna systems. When non-orthogonal training sequences are used for uplink training, the paper shows that the precoding matrix used by the base station in one cell becomes corrupted by the channel between that base station and the users in other cells in an undesirable manner. This paper analyzes this fundamental problem of pilot contamination in multi-cell systems. Furthermore, it develops a new multi-cell MMSE-based precoding method that mitigates this problem. In addition to being linear, this precoding method has a simple closed-form expression that results from an intuitive optimization. Numerical results show significant performance gains compared to certain popular single-cell precoding methods.

N. B. Mehta et al [14] proposes a simple, novel, and general method is presented in this paper for approximating the sum of independent or arbitrarily correlated lognormal random variables (RV) by a single lognormal RV. The method is also shown to be applicable for approximating the sum of lognormal-Rice and Suzuki RVs by a single lognormal RV. A sum consisting of a mixture of the above distributions can also be easily handled. The method uses the moment generating function (MGF) as a tool in the approximation and does so without the extremely precise numerical computations at a large number of points that were required by the previously proposed methods in the literature. Unlike popular approximation methods such as the Fenton-Wilkinson method and the Schwartz-Yeh method, which have their own respective short-comings, the proposed method provides the parametric flexibility to accurately approximate different portions of the lognormal sum distribution. The accuracy of the method is measured both visually, as has been done in the literature, as well as quantitatively, using curve-fitting metrics. An upper bound on the sensitivity of the method is also provided.

A. F. Molisch [15] provides an in-depth analysis of current treatment of the area, addressing both the traditional elements, such as Rayleigh fading, BER in flat fading channels, and equalisation, and more recently emerging topics such as multi-user detection in CDMA systems, MIMO systems, and cognitive radio. The dominant wireless standards; including cellular, cordless and wireless LANs; are discussed. Topics featured include: wireless propagation channels, transceivers and signal processing, multiple access and advanced transceiver schemes, and standardised wireless systems. Combines mathematical descriptions with intuitive explanations of the physical facts, enabling readers to acquire a deep understanding of the subject. Includes new chapters on cognitive radio, cooperative communications and relaying, video coding, 3GPP Long Term Evolution, and WiMax; plus significant new sections on multi-user MIMO, 802.11n, and information theory. Companion website featuring: supplementary material on 'DECT', solutions manual and presentation slides for instructors, appendices, list of abbreviations and other useful resources.

G. L. Stuber [16] proposes a mathematically rigorous overview of physical layer wireless communications is now in a 4th, fully revised and updated edition. The new edition features new content on 4G cellular systems, 5G cellular outlook, band pass signals and systems, and polarization, among many other topics, in addition to a new chapters on channel assignment techniques. Along with coverage of fundamentals and basic principles sufficient for novice students, the volume includes finer details that satisfy the requirements of graduate students aiming to conduct in-depth research. The book begins with a survey of the field, introducing issues relevant to wireless communications. The book moves on to cover relevant discrete subjects, from radio propagation, to error probability performance, and cellular radio resource management. An appendix provides a tutorial on probability and random processes. The content stresses core principles that are applicable to a broad range of wireless standards. New examples are provided throughout the book to better explain the more complex material to the reader. Additional problems have also been added to those already appearing at the ends of the chapters to make the book more suitable for course instruction.

B.Wang [17] presents massive multiple-input-multiple-output (MIMO) wireless communications refers to the idea equipping transmitters with a very large number of antennas and has been shown to potentially allow for orders of magnitude improvement in spectral and energy efficiency using relatively simple (linear) processing. In this letter, we consider a scenario that multiple links transmit in the vicinity of each other simultaneously using the same time-frequency resource. With the limitations of an infinite number of antennas for the receiver at each link, we use minimum-mean-squared-error (MMSE) receivers to suppress the interference. The asymptotic signal to interference and noise ratio (SINR) at each link's receiver is analyzed by using matrix theory. In addition, we find substitute beamforming methods to achieve the same performance compared to the MMSE receiver when massive MIMO is used. Finally, the upper and lower bounds on the SINR in the limit of nonideal channel conditions are derived.

N. Kim [18] considers the uncoded multiple-input multiple-output (MIMO) system with linear minimum mean square error (MMSE) detection under ideal fast fading. The distribution of SINR at the output of the MMSE detection is derived for a small number of transmit and receive antennas. We present new approximation for the Gaussian Q-function driven by numerical simulation. Based on the SINR distribution and new approximation for Q-function, we analyze the performance of linear MMSE detection under ideal fast fading environment. By comparing the analytical results and Monte Carlo simulated results, we validate the analytical results.

A. Kammoun [19] presents study of the linear minimum mean squared error (LMMSE) estimator for multidimensional signals in the large-dimension regime. Such an estimator is frequently encountered in wireless communications and in array processing, and the signal-to-interference-plus-noise ratio (SINR) at its output is a popular performance index. The SINR can be modeled as a random quadratic form which can be studied with the help of large random matrix theory, if one assumes that the dimension of the received and transmitted signals go to infinity at the same pace. This paper considers the asymptotic behavior of the SINR for a wide class of multidimensional signal models that includes general multiple-antenna as well as spread-spectrum transmission models. The expression of the deterministic approximation of the SINR in the large-dimension regime is recalled and the SINR fluctuations around this deterministic approximation are studied. These fluctuations are shown to converge in distribution to the Gaussian law in the large-dimension regime, and their variance is shown to decrease as the inverse of the signal dimension.

A. Kammoun [20] presents study of the performance of the linear minimum mean-square error (LMMSE) receiver for (receive) correlated multiple-input multiple-output (MIMO) systems. By the random matrix theory, it is well known that the signal-to-noise ratio (SNR) at the output of this receiver behaves asymptotically like a Gaussian random variable as the number of receive and transmit antennas converge to +infin at the same rate. However, this approximation being inaccurate for the estimation of some performance metrics such as the bit error rate (BER) and the outage probability, especially for small system dimensions, Li proposed convincingly to assume that the SNR follows a generalized gamma distribution which parameters are tuned by computing the first three asymptotic moments of the SNR. In this paper, this technique is generalized to (receive) correlated channels, and closed-form expressions for the first three asymptotic moments of the SNR are provided. To obtain these results, a random matrix theory technique adapted to matrices with Gaussian elements is used. This technique is believed to be simple, efficient, and of broad interest in wireless communications. Simulations are provided, and show that the proposed technique yields in general a good accuracy, even for small system dimensions.

A research by M. Wu [21] presents Large-scale (or massive) multiple-input multiple-out put (MIMO) is expected to be one of the key technologies in next-generation multi-user cellular systems based on the upcoming 3GPP LTE Release 12 standard, for example. In this work, we propose-to the best of our knowledge-the first VLSI design enabling high-throughput data detection in single-carrier frequency-division multiple access (SC-FDMA)-based large-scale MIMO systems. We propose a new approximate matrix inversion algorithm relying on a

Neumann series expansion, which substantially reduces the complexity of linear data detection. We analyze the associated error, and we compare its performance and complexity to those of an exact linear detector. We present corresponding VLSI architectures, which perform exact and approximate soft-output detection for large-scale MIMO systems with various antenna/user configurations. Reference implementation results for a Xilinx Virtex-7 XC7VX980T FPGA show that our designs are able to achieve more than 600 Mb/s for a 128 antenna, 8 user 3GPP LTE-based large-scale MIMO system. We finally provide a performance/complexity trade-off comparison using the presented FPGA designs, which reveals that the detector circuit of choice is determined by the ratio between BS antennas and users, as well as the desired error-rate performance.

A research conducted by X. Gao [22] presents the minimum mean square error (MMSE) signal detection algorithm is near-optimal for uplink multi-user large-scale multiple-input-multiple-output (MIMO) systems, but involves matrix inversion with high complexity. It is firstly proved that the MMSE filtering matrix for large-scale MIMO is symmetric positive definite, based on which a low-complexity near-optimal signal detection algorithm by exploiting the Richardson method to avoid the matrix inversion is proposed. The complexity can be reduced from $O(K^3)$ to $O(K^2)$, where K is the number of users. The convergence proof of the proposed algorithm is also provided. Simulation results show that the proposed signal detection algorithm converges fast, and achieves the near-optimal performance of the classical MMSE algorithm.

A study proposed by X. Gao [23] presents optical wireless communication (OWC) has been a rapidly growing research area in recent years. Applying multiple-input multiple-output (MIMO), particularly large-scale MIMO, into OWC is very promising to substantially increase spectrum efficiency. However, one challenging problem to realize such an attractive goal is the practical signal detection algorithm for optical MIMO systems, whereby the linear signal detection algorithm like minimum mean square error (MMSE) can achieve satisfying performance but involves complicated matrix inversion of large size. In this paper, we first prove a special property that the filtering matrix of the linear MMSE algorithm is symmetric positive definite for indoor optical MIMO systems. Based on this property, a low-complexity signal detection algorithm based on the successive over relaxation (SOR) method is proposed to reduce the overall complexity by one order of magnitude with a negligible performance loss. The performance guarantee of the proposed SOR-based algorithm is analyzed from the following three aspects. First, we prove that the SOR-based algorithm is convergent for indoor large-scale optical MIMO systems. Second, we prove that the SOR-based algorithm with the optimal relaxation parameter can achieve a faster convergence rate than the recently proposed Neumann-based algorithm. Finally, a simple quantified relaxation parameter, which is independent of the receiver location and signal-to-noise ratio, is proposed to guarantee the performance of the SOR-based algorithm in practice. Simulation results verify that the proposed SOR-based algorithm can achieve the exact performance of the classical MMSE algorithm with a small number of iterations.

L. Dai [24] suggested for uplink large-scale multiple-input-multiple-output (MIMO) systems, the minimum mean square error (MMSE) algorithm is near optimal but involves matrix inversion with high complexity. In this paper, we propose to exploit the Gauss-Seidel (GS) method to iteratively realize the MMSE algorithm without the complicated matrix inversion. To further accelerate the convergence rate and reduce the complexity, we propose a diagonal-approximate initial solution to the GS method, which is much closer to the final solution than the traditional zero-vector initial solution. We also propose an approximated method to compute log-likelihood ratios for soft channel decoding with a negligible performance loss. The analysis shows that the proposed GS-based algorithm can reduce the computational complexity from $O(K^3)$ to $O(K^2)$, where K is the number of users. Simulation results verify that the proposed algorithm outperforms the recently proposed Neumann series approximation algorithm and achieves the near-optimal performance of the classical MMSE algorithm with a small number of iterations.

D. L. Donoho [25] proposed a new class of low-complexity iterative thresholding algorithms for reconstructing sparse signals from a small set of linear measurements. The new algorithms are broadly referred to as AMP, for approximate message passing. This is the first of two conference papers describing the derivation of these algorithms, connection with the related literature, extensions of the original framework, and new empirical evidence. In particular, the present paper outlines the derivation of AMP from standard sum-product belief propagation, and its extension in several directions. We also discuss relations with formal calculations based on statistical mechanics methods.

A study proposed by C. Jeon [26] presents optimal data detection in multiple-input multiple-output (MIMO) communication systems with a large number of antennas at both ends of the wireless link entails prohibitive computational complexity. In order to reduce the computational complexity, a variety of sub-optimal detection algorithms have been proposed in the literature. In this paper, we analyze the optimality of a novel data-detection method for large MIMO systems that relies on approximate message passing (AMP). We show that our algorithm, referred to as individually-optimal (IO) large-MIMO AMP (short IO-LAMA), is able to perform IO data detection given certain conditions on the MIMO system and the constellation set (e.g., QAM or PSK) are met.

S. J. Wright [27] led a research on coordinate descent algorithms solve optimization problems by successively performing approximate minimization along coordinate directions or coordinate hyperplanes. They have been used in applications for many years, and their popularity continues to grow because of their usefulness in data analysis, machine learning, and other areas of current interest. This paper describes the fundamentals of the coordinate descent approach, together with variants and extensions and their convergence properties, mostly with reference to convex objectives. We pay particular attention to a certain problem structure that arises frequently in machine learning applications, showing that efficient implementations of accelerated coordinate descent algorithms are possible for problems of this type. We also present some parallel variants and discuss their convergence properties under several models of parallel execution.

M. Bayati [28] presents approximate message passing (AMP) algorithms have proved to be effective in reconstructing sparse signals from a small number of incoherent linear measurements. Extensive numerical experiments further showed that their dynamics is accurately tracked by a simple one-dimensional iteration termed state evolution. In this paper, we provide rigorous foundation to state evolution. We prove that indeed it holds asymptotically in the large system limit for sensing matrices with independent and identically distributed Gaussian entries. While our focus is on message passing algorithms for compressed sensing, the analysis extends beyond this setting, to a general class of algorithms on dense graphs. In this context, state evolution plays the role that density evolution has for sparse graphs. The proof technique is fundamentally different from the standard approach to density evolution, in that it copes with a large number of short cycles in the underlying factor graph. It relies instead on a conditioning technique recently developed by Erwin Bolthausen in the context of spin glass theory.

Y. Nesterov [29] proposes new methods for solving huge-scale optimization problems. For problems of this size, even the simplest full-dimensional vector operations are very expensive. Hence, we propose to apply an optimization technique based on random partial update of decision variables. For these methods, we prove the global estimates for the rate of convergence. Surprisingly enough, for certain classes of objective functions, our results are better than the standard worst-case bounds for deterministic algorithms. We present constrained and unconstrained versions of the method, and its accelerated variant. Our numerical test confirms a high efficiency of this technique on problems of very big size.

J. Choi [30] proposes statistical eigen-beamforming is shown to be effective over a spatially correlated fading channel. In the paper, we investigate the use of the statistical eigen-beamforming with short-term selection for an orthogonal frequency-division multiplexing (OFDM) downlink. The contributions of the paper are as follows: (1) an efficient statistical eigen-beamforming method with limited feedback for OFDM has been proposed; and (2) exact and asymptotic expressions of the average bit error rate for (transmitter side) spatially correlated Rayleigh fading channels are derived. In particular, the asymptotic expression allows us to gain insight to statistical eigen-beamforming with selection diversity in terms of array gain and diversity order.

L. Bai [31] proposes a low-complexity approach for the large-scale (underdetermined) multiple-input multiple-output (MIMO) detection is proposed using the Markov chain Monte Carlo (MCMC) algorithm in conjunction with blockwise sampling. Klein's algorithm is employed in each sub-system to draw multidimensional samples for an MCMC detector in iterative detection and decoding (IDD). From analysis, we find that the lattice reduction (LR) technique cannot improve the performance of the proposed MCMC-based approach under low-correlated channel environment. In addition, due to blockwise sampling, the proposed method exhibits a faster convergence speed when running a Markov chain and provides a near-optimal performance for the detection of underdetermined MIMO systems. Complexity analysis and simulation results show that the proposed approach outperforms the conventional LR-based Klein randomized successive interference cancellation (SIC) detection with a relatively low complexity.

B. E. Godana [32] presents parametrization of unitary matrices using Givens rotations has been used for limited feedback in multiple-input multiple-output (MIMO) systems. Feedback based on these rotations has been adopted in IEEE 802.11n and other upcoming standards. However, the probability distributions of Givens rotations is not known for correlated channels, forcing the use of uniform quantization. In this paper, novel probability density function (PDF) models, based on beta and wrapped Cauchy distributions, are proposed for Givens rotations in correlated MIMO channels. Empirical distributions and goodness-of-fit tests show that the proposed distributions characterize the spatial correlation behavior with good accuracy. Moreover, it is shown that the distributions known in the literature for uncorrelated MIMO channels are only special cases. Distributions of Givens rotations are useful to understand the behavior of singular vectors of correlated channels. In this paper, the PDF models are utilized for bit allocation and optimized codebook design. Simulations show that precoding using the proposed codebooks achieves significant performance improvement, in terms of mean square error and sum rate, as compared to using uniform codebooks. It is also shown that the bit allocations proposed in this paper reduce to that of IEEE 802.11n standard when the MIMO channel is not spatially correlated.

A. Burg [33] proposes multiple-input multiple-output (MIMO) techniques are a key enabling technology for high-rate wireless communications. This paper discusses two ASIC implementations of MIMO sphere decoders. The first ASIC attains maximum-likelihood performance with an average throughput of 73 Mb/s at a signal-to-noise ratio (SNR) of 20 dB; the second ASIC shows only a negligible bit-error-rate degradation and achieves a throughput of 170 Mb/s at the same SNR. The three key contributing factors to high throughput and low complexity are: depth-first tree traversal with radius reduction, implemented in a one-node-per-cycle architecture, the use of the /spl lscr//sup /spl infin//-instead of /spl lscr//sup 2/-norm, and, finally, the efficient implementation of the enumeration approach recently proposed in . The resulting ASICs currently rank among the fastest reported MIMO detector implementations.

J. Jaldén [34] proposes sphere decoding has been suggested by a number of authors as an efficient algorithm to solve various detection problems in digital communications. In some cases, the algorithm is referred to as an algorithm of polynomial complexity without clearly specifying what assumptions are made about the problem structure. Another claim is that although worst-case complexity is exponential, the expected complexity of the algorithm is polynomial. Herein, we study the expected complexity where the problem size is defined to be the number of symbols jointly detected, and our main result is that the expected complexity is exponential for fixed signal-to-noise ratio (SNR), contrary to previous claims. The sphere radius, which is a parameter of the algorithm, must be chosen to ensure a non vanishing probability of solving the detection problem. This causes the exponential complexity since the squared radius must grow linearly with problem size. The rate of linear increase is, however, dependent on the noise variance, and thus, the rate of the exponential function is strongly dependent on the SNR. Therefore sphere decoding can be efficient for some SNR and problems of moderate size, even though the number of operations required by the algorithm strictly speaking always grows as an exponential function of the problem size.

CHAPTER-3

BASIC UNDERSTANDING OF MIMO SYSTEMS

3.1 Introduction

Multiple Input Multiple Output (MIMO) communications techniques have been studied from a long time approximately more than one decade. it has been proved that theoretically that Communication system that use multiple antennas at both the transmitter and receiver have been the subject of much recent research because theoretically they offer improved capacity, coverage, reliability, or combinations compared to systems with a single antenna at either the transmitter or receiver or both. MIMO also offer different benefits, namely beam forming gain, spatial diversity and multiplexing. With beam forming, transmit and receive antenna patterns can be focused into a specific angular direction by the choice of complex baseband antenna weight. Under line-of-sight (LOS) channel conditions, X R and X T gains add up, leading to an upper limit of m.n for the beam forming gain of a MIMO system (n and m here the number of antenna elements for the receiver Rx and for the transmitter X T respectively). The increasing demand for capacity in wireless systems has motivating research aimed at achieving higher throughput on a given bandwidth. One important finding of this activity is that for an environment sufficiently rich in multipath components, the wireless channel capacity can be increased using multiple antennas on both transmit and receive sides of the link.

3.2 MIMO Systems

The very basic first idea about MIMO (Multiple-input-Multiple-output) system found in the work of AR Kaye and DA George (1970), Branderburg and Wyner (1974), and W.Van Etten (1975,1976) during the working on beam-forming application. The MIMO system first time introduced at Stanford University in 1994 and later at Lucent in 1996. Various authors purposed a various principal of MIMO system. Richard Roy and Bjorn Ottersten were proposed the SDMA (space division multiple access) concept of MIMO in 1991.While in 1993 Arogyaswami Paulraj proposed SM (spatial multiplexing) concept. In 1996 Greg der Raleigh and Gerard J. Foschini proposed new approach as in the one transmitter for improvise the link in effect we have to use more than one antenna in transmitter side which are co-located. The function of

MIMO can be classified into three different categories which are

1. Precoding

2. Spatial multiplexing

3. Diversity coding

Precoding- in the narrow sense precoding is multi-stream beam forming. While in the wider sense precoding consider all spatial processing which occur on transmitter. In single stream beamforming, we send same signal from each transmit transmitter and we take phase and gain of transmitted signals in such a way that it can maximize the signal power at the receiver. Beamforming used to add emitted signal from the transmitted antenna for increasing the gain of the signal which received at receiver. In Line-of-Sight (LOS) propagation, beamforming provide intensive explained direction pattern but for the cellular network conventional beam does not provide a good idea because it characterize by multipath propagation. When we arrange receiver with multiple antennas, transmit beamforming are not able to provide maximum signal strength among all receiver antennas, at this stage precoding generally favorable. Precoding required the knowledge of channel state information at both end of communication system. Spatial multiplexing- It require MIMO antenna system. In spatial multiplexing, high rate stream signal split in multiple low rate streams. Each stream transmits from different transmitter in same frequency channel. Spatial multiplexing used to increase the channel capacity at high signal to noise ratio. With the help of number of antennas which used at both and of communication link we can limit the maximum number of spatial stream. We can use spatial multiplexing without CSI at transmitter but if we want to use it with precoding we have require CSI. Diversity Coding- we used it when we have no knowledge of channel at transmitter. In this method, we transmit a single stream where we code the signal with the help of space-time coding. Diversity coding exploits independent fading to enhance the diversity of signal in multiple antenna system. If we have some knowledge of channel at transmitter, we can combine diversity coding with spatial multiplexing.

3.3 Different forms of MIMO

One is multi-antenna type called it as single user type. The special case of MIMO is SISO (single-input-single-output), SIMO (single-input-multiple-output), MISO (multiple -input-multiple -output). In MISO case receiver used only one antenna. While in SIMO case transmitter used only one antenna. The established/former radio system is a perfect example of SISO system. The SISO systems use single antenna at both transmitter and receiver. The some limitation on case is we have to select large physical antenna spacing.

Another is multi-user type. In the recent research, it found that multi-user (also called Network MIMO) can have high potential practically. Cooperative MIMO, multi-user MIMO are some class of multiuser type.

3.4 Mathematical Description of MIMO System

Basically MIMO stands for multiple inputs multiple outputs. It means multiple antennas on both the side of communication system which is transmitter and receiver.

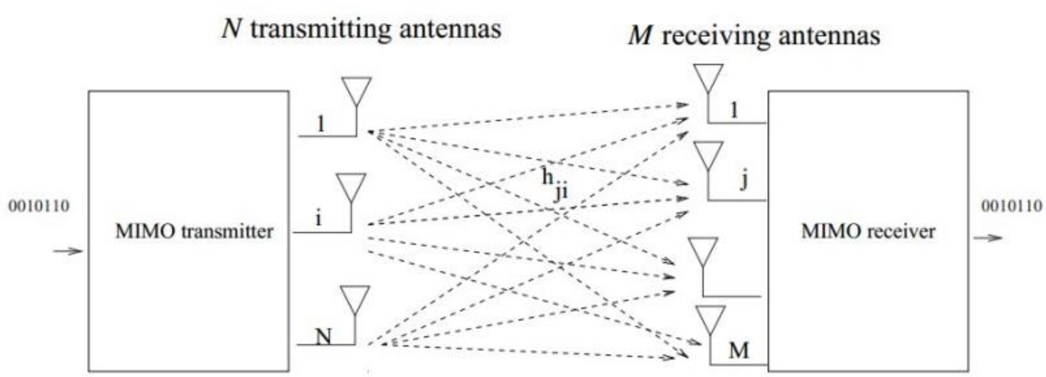


Fig. 3.1 Block diagram of MIMO system

Fig. 3.1 show above is the basic MIMO Channel block diagram. It shows multiple transmitters at transmit location and multiple receivers at receive location. The MIMO systems are able to increase the capacity of the communication channel in which the signals propagate. The channel matrix for the MIMO systems can be represents a

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1M} \\ h_{21} & h_{22} & \cdots & h_{2M} \\ \vdots & & \ddots & \vdots \\ h_{N1} & \cdots & \cdots & h_{NM} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_M \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_N \end{bmatrix}$$

The format of channel matrix which is providing in equation (1.1) shows the many elements in between transmitter and receiver. These elements are channel gains or complex fading coefficient between transmitter and receiver. We are assuming here that the gains are independent and identically distributed and based on Gaussian random variable have zero mean and unit variance. We are transmitting frame by frame. In between the frame the channel does not change. When the frame of transmitted signal are change the channel are also change. In between the communication system when the channel travels so many obstacles presents which makes the multipath for input transmission signal. So, the received signal at the receiver is the sum of these entire multipath signals.

From the information theory, we can represent the channel capacity of MIMO System when the transmitter and the receiver kept instant channel state information as

$$C_{Perfect-csi} = E\left[\max \log_{2\det}(I + \rho HQH^{H})\right] = E[og_{2}\det(I + \rho DSD) \qquad (1.1)$$

Where H () = Hermitian transpose

$\rho =$ Transmit SNR (ratio between transmit power and noise power)

We can achieve optimal covariance of the signal) (Q=VSV^{H}) by singular value decomposition (SVD) of the channel matrix $(UDV^{H} = H)$ and optimal diagonal power allocation matrix). $(S = daig(s_1........, s_{\min}(N_t, N_r)0,.........,0)$ We can achieve optimal power allocation by water filling which is

$$S_1 = \left(\mu - \frac{1}{\rho d_1^2}\right) i = 1,......, \min(N_t, N_r) \qquad (1.2)$$

Where $d_1,......, d_{\min(N_t, N_r)}$ = Diagonal element of D Is zero if its argument is negative. We select μ in prenominal way that it satisfy $S_1 + ... + S_{\min(N_t N_r) = N_t}$ If transmitter kept only statistical channel state information then the channel capacity will decrease. The capacity decreases as signal covariance Q could only optimize in terms of average mutual information

$$C_{statistied-CSI} = \max^{E[\log_2 \det(I + \rho HQH^h)} \qquad (1.3)$$

With the statistical information the correlation affect the channel capacity. if transmitter is no channel state information. It can select signal covariance Q for maximize channel capacity.

This take place under worst-case statistics that means $Q = \frac{1}{N_t} I$

$$C_{no-CSI} = E\left[\log_2 \det(I + \frac{\rho}{N_t} HH^{hH})\right] \tag{1.4}$$

With the statistical properties of channel, channel capacity is no more than) ,min (N_t ,N_r) times greater than of a SISO system.

3.5 Advantages of MIMO antenna system

Wireless channel provide some limitation in communication system which is shown below in Fig 1.2 and explained. In the wireless transmission the major limitations are

1. Noise: Thermal noise create problem in transmission which effect on electronic instruments. By this the efficiency of instruments gets low. Also by the increased noise the noise power increased which reduced the signal to noise ratio and by this effect the signal to noise ratio reach in limited state. By the noise affect the strength of signal increase or decrease in a random manner.

2**.** CCI: CCI stands for co-channel interference. It is a cross talk on different transmitter on the same radio frequency. During poor weather we can see this effect on cellular communication. It mainly occurs when the radio frequency distribution has some problem and radio spectrum provide adverse effect by crowded scenario. When we allocate the radio spectrum in a right manner than this problem can be decrease.

3**.** ISI: It stands for inter symbol interference. It occurs mostly in telecommunication. In the communication system when we transmit the signal from the transmitter then in between the signal interface with other signal. This interference occurs in symbols of signals. It produced distortion like noise. It also occurs on multipath propagation and band limited signal. ISI effects on eye pattern. In band-limited signal it can be avoided by pulse shaping. The ISI can be minimizing by making impulse response so smaller. By the minimization of impulse response the transmitted bit are not able to overlap.

4. Fading: In the communication system fading refers the decrease in the signal strength. Fading

is a random phenomenon, so it does not depend on time. Either by multipath propagation or by wave propagation it comes. Fading classified into different category like slow and fast fading, selective and frequency selecting fading etc. fading effect changes the amplitude and phase of transmitted signal. MIMO systems which used at both transmitter and receiver side are capable to reduce all these limitation in a certain extend. Due to gain of spatial multiplexing the communication channel capacity improves. The increased capacity does not take more power as well as bandwidth

While by the diversity gain we can see the improvement in reliability. By the antenna array system the output signal to noise ratio is more than N times input signal while N stands for noise power. So we can see that by these and by many more parameter increases many limitation of wireless communication.

We used MIMO system mostly in wireless communication (WLAN, Wi-Fi, WI-Max). The MIMO system has the capacity in the improvement of data while the distance between antennas, signal strength, noise in the environment are major concern. The channel capacity has some limit. This limit is shown by Shannon in his theorem which is

$$\text{Capacity} = BW\log_2 (1+SNR) \qquad (1.5)$$

By this equation it is clear that the channel capacity is ultimate depends upon channel Bandwidth and signal to noise ratio. The signal bandwidth can be increased by bit-rate/symbol rate of modulating signal. The MIMO antennas system used multiple antennas at transmitter as well as receiver. By this increased antennas model not only we can improve our channel capacity but high data rate also. For example the 4 x 4 antenna system produce double spatial stream compared to 2 x 2 antennas system as well as by four times compared to 1 x 1 antennas system. The 1 x 1 antennas system called the traditional antennas system.

3.5.1 The Benefits of MIMO

1. It has under water application as sonar communication.

2. It is used in RADAR application, it increase the Beam-forming.

3. It can be used as Broadband.

4. It can be used in multimedia cases alike video and more many.

5. It can also use in home, office, moving object and moving to stationary object.

6. It has the ability to provide multiplexing gain.

7. It can increase the signal to noise ratio by some constant factor.

8. We can get the maximum diversity gain by MIMO system.

9. In the capacity issue the SISO (single input-single output) based on SNR. While in MIMO cases the capacity improved by less antennas. The growth rate of capacity in MIMO is linear compared to SISO.

10. The MIMO use less power for transmission. It removes the interference in the channel and increases the signal strength. By the increased strength of signal the signal provide better efficiency. The users and ranges are also improved.

3.6 Challenges in MIMO system

1. Larger MIMO- more than hundred low power antenna (approximately 1mW) places on a Base station to increase the performance of MIMO system.

2. Estimation of practical impairment- in practical communication system major factor like timing offset, phase shift, frequency offset affect the system performance. The estimation of these several factors as well as the compensation of these factors is a major challenge

3. MIMO relaying network- Combined the cooperative and MIMO technologies to increase the channel capacity, coverage area and channel reliability

4. Reduce the hardware and software complexity, thermal problem due to increase antenna structure on both side of antenna of the MIMO system

5. Reduce the Antenna spacing problem which occur difficulty in MIMO communication.

6. Heterogeneous network- combined the macro-cell, Pico-cell and feta-cell together to increase indoor coverage as well as power efficiency

7. Multicell MIMO- equipped multiple base stations with multiple antenna is a main challenge in interference mitigation

8. Reduce the problem of power consumption

CHAPTER-4

SYSTEM MODEL FOR MULTI-USER MASSIVE MIMO SYSTEMS

In this chapter, we develop the system model for a very large scale multi-user MIMO system operating under a composite fading environment. The small-scale fading arises due to the presence of multiple propagation paths between the transmitter and the receiver. The difference in the propagation delay of each path causes a change in the phase of the waves arriving at the receiver antennas. This change of phase causes the received signals from the multiple paths to undergo constructive or destructive interference at the receiver. The large-scale fading is caused by the presence of an obstacle in the propagation path and depends on the environmental surroundings and the transmitter-receiver separation distance. The two types of fading are responsible for fluctuations in the received power. The small-scale fading causes rapid fluctuations in the received power over a short interval of time or a short travel distance whereas the large-scale fading defines the local mean of the received power at a specific transmitter-receiver distance. As the distance changes significantly or the propagation path is obstructed by an obstacle, the large-scale fading causes the local mean of the received power to deviate sufficiently from its previous value, thus defining a new local mean for that specific propagation scenario. The large-scale fading varies slowly with time.

In this thesis, we choose Rayleigh fading model to represent the small-scale fading (simply known as fading) whereas the large-scale fading (also referred to as shadowing) is modeled via lognormal distribution [15], [16]. In section 4.1, we develop a mathematical model of the wireless channel under composite Rayleigh fading-lognormal shadowing environment and in section 5.2, we formulate the received SINR for a multi-user massive MIMO system.

4.1 Channel Model

We consider the uplink of a single cell multi-user massive MIMO system where a BS is equipped with M antennas. The BS receives the data from K single-antenna users in the same time-frequency resource. These transmissions are corrupted by the channel impairments. The transmissions from K users to the BS suffer from independent Rayleigh fading and lognormal shadowing. The M×1 received signal vector at the BS is given by

$$y = \sqrt{P_t}Gx + n, \tag{4.1}$$

where G represents the M×K channel matrix between the K users and the M BS antennas, P_t is the average transmit power of a single user, x is the vector of symbols transmitted simultaneously by K users and n is the noise vector.

The channel matrix G models Rayleigh fading and lognormal shadowing. The channel coefficient g_{ik} between the ith BS antenna and the kth user can be represented as

$$g_{ik} = h_{ik}\sqrt{v_k} \tag{4.2}$$

where h_{ik} is the small-scale fading coefficient between the ith BS antenna and the kth user and v_k represents the large-scale fading of the kth user such that $v_k \sim \log N\,(\mu_{(dB)}, \sigma^2_{(dB)})$. In a Rayleigh fading environment, the small-scale fading coefficient h_{ik} follows a complex normal distribution with zero mean and unit variance i.e., $h_{ik} \sim CN(0,1)$.

Since the BS antennas are closely spaced, the large-scale fading for a single user across M BS antennas is correlated. However, the small-scale fading coefficients are independent and identically distributed (i.i.d). In this thesis, we assume perfect correlation between the shadowing components of a single user across M BS antennas. Therefore, the received signals from the kth user across M BS antennas suffer identical shadowing. The channel matrix G is then given by

$$G = HV^{1/2}, \tag{4.3}$$

where H is the M×K matrix of small-scale fading coefficients between the M BS antennas and K users and V is a K×K diagonal matrix containing the large-scale fading coefficients of K users. By using a linear detector, the received signal y is processed as

$$r = A^H y. \tag{4.4}$$

The vector r in (4.4) gives the received signals from all the users where A is the linear detector matrix that depends on the channel matrix G and H is the Hermitian operator.

4.2 SINR Formulation

After applying the linear detector and from (4.4), the received signal vector is given by

$$r = \sqrt{P_t} A^H G x + A^H n. \tag{4.5}$$

To formulate the SINR of a single user, the vector r is decomposed into two parts. Let r_j and x_j represent the received signal and the transmitted symbol of the j_{th} user, respectively. Then

$$r_j = \sqrt{P_t} a_j^H g_j x_j = \sqrt{P_t} \sum_{k=1, k\neq j}^{K} a_j^H g_k x_k + a_j^H n, \tag{4.6}$$

where a_j and g_j represent the j_{th} columns of the matrices A and G, respectively. The first term in (4.6) represents the desired signal of the j_{th} user, whereas the other two terms constitute interference from other users and noise, respectively. Without the loss of generality, we assume unit power spectral density of noise. The SINR of the jth user can then be represented as

$$SINR_j = \frac{P_t \left| a_j^H g_j \right|^2}{P_t \sum_{k=1, k\neq j}^{K} \left| a_j^H g_k \right|^2 + \left\| a_j \right\|^2}. \tag{4.7}$$

where $\|.\|$ represents the 2-norm of a vector and $|.|$ denotes the absolute value of a vector.

4.3 Fading Distributions

4.3.1 Rayleigh fading Distribution

In a rich scattering environment, if there is no dominant line-of-sight path between the transmitter and the receiver, the magnitude, R, of the received signal's complex envelope follows a Rayleigh distribution. The PDF of the Rayleigh distribution is given by

$$P_R(r) = \frac{2r}{\Omega_p} \exp\left(-\frac{r^2}{\Omega_p}\right), \qquad r \geq 0.$$

(4.8)

where Ω_p is the average envelope power. In terms of channel coefficients, the magnitude of complex envelope can be written as R = $|h_{ik}|$.

In wireless communications, the corresponding squared envelope of the received signal is of considerable importance as it is directly proportional to the received power and thus, represents the received SNR. The square of a Rayleigh RV is an exponential RV. The squared envelope, R^2, thus follows an exponential distribution with the PDF given by

$$P_{R^2} = \frac{1}{\Omega_p} \exp\left(-\frac{r}{\Omega_{\mathrm{p}}}\right), \qquad r \geq 0. \tag{4.9}$$

For simulation purposes, the average envelope power has to be kept unity. Therefore, we assume $\Omega_p = 1$ throughout the thesis. The distribution of the squared envelope can then be represented as $|h_{ik}|^2 \sim Exp(1)$.

4.3.2 Lognormal Shadowing Distribution

Practical measurements have shown that the local mean of the received power follows a lognormal distribution, therefore, the received squared envelope due to shadowing in wireless communications is often modeled by a lognormal RV. The PDF of the lognormal distribution is given by

$$P_V(v) = \frac{\xi}{v\sigma_{dB}\sqrt{2\pi}} \exp\left(-\frac{(\xi \log_e v - \mu_{(dB)})^2}{2\sigma_{(\mathrm{dB})}}\right) \tag{4.10}$$

Where $\xi = 10/\log_e 10$ is a scaling constant and $\sigma_{(dB)}$ is the shadow standard deviation. The lognormal RV, V, in (5.10) is defined as $V = 10^{0.1X}$ such that $X \sim N(\mu_{(dB)}, \sigma^2_{(dB)})$. The typical value of $\sigma_{(dB)}$ lies between 4 dB and 12 dB. The higher the value of $\sigma_{(dB)}$, the more severe the shadowing is.

CHAPTER-5

RECEIVER DESIGN ANALYSIS

5.1 Analysis of MRC Receiver:

In telecommunication, maximal-ratio combining is a method of diversity combining in which

(a) The signals from M branches are weighted according to their individual signal voltage to noise power ratios & then summed.

(b) Before being summed, individual signals must be co phased which generally requires individual receiver & phasing circuit for each antenna element.

(c) MRC produces an output with an acceptable SNR equal to sum of individual SNR's.

(d) In Maximum Ratio Combining (MRC) amplitudes and phases of the data signals received are adjusted with the help of digital signal processing in such a way that signal addition leads to gains in the S/N ratio and hence to a better bit error ratio (BER).

In this section, we analyze the MRC receiver for a very large scale multi-user MIMO system under a composite-fading environment. We use (4.7) in the context of an MRC receiver to analyze the SINR.

In case of perfect channel state information (CSI), the M × K linear detector matrix A for an MRC receiver is given by A = G hence, $a_j = g_j$. From (4.3) and (4.7), we obtain the SINR of a single user for an MRC receiver as

$$SINR_j^{mrc} = \frac{P_t \left\| h_j \right\|^4 v_j^2}{P_t v_j \sum_{k=1,k\neq j}^{K} \left| \hbar_j^H h_k \right|^2 v_k + \left\| h_j \right\|^2 v_j}$$

$$\triangleq \frac{P_t \left\| h_j \right\|^2 v_j}{P_t \sum_{k=1,k\neq j}^{K} \frac{\left| h_j^H h_k \right|^2}{\left\| h_j \right\|^2} v_k + 1}. \tag{5.1}$$

Conditioned on h_j, we define a new RV $g_k$such that $g_k = \frac{\left|h_j^H h_k\right|}{\|h_j\|}$. $g_k$is a Gaussian RV with zero mean and unit variance that is independent of h_j. Therefore, $g_k \sim CN(0,1)$. From (5.1), the SINR is then given by

$$SINR_j^{mrc} = \frac{P_t\|h_j\|^2 v_j}{P_t \sum_{k=1,k\neq j}^{K}|g_k|^2 v_k + 1}. \tag{5.2}$$

5.1.1 SNR of MRC Receiver:

The numerator in (5.2) is the SNR, Z, of a single user at the BS. For notational simplicity, we omit the subscripts in the expression of Z. Therefore,

$$Z = P_t v \sum_{i=1}^{M}|h_i|^2 \coloneqq P_t v\, \gamma, \tag{5.3}$$

where $\gamma \sim \Gamma(M, 1)$ owing to the sum of independent and identically distributed exponential RVs each having a unit mean.

From (5.3), it is evident that the SNR follows a gamma-lognormal product distribution. The PDF of a gamma RV is given by

$$P_G(\gamma) = \frac{\gamma^{M-1}\exp(-\gamma)}{\Gamma(M)}, \tag{5.4}$$

where $\Gamma(\mathrm{M}) = (\mathrm{M}-1)!$ since M is an integer. The distribution of a product RV, Z=VG, is given by

$$P_Z(z) = \int_{-\infty}^{\infty} P_V(v) P_G\left(\frac{z}{v}\right)\frac{1}{|v|}\,dv. \tag{5.5}$$

Since, P_i is a constant, therefore, we neglect it in the PDF expression of gamma-lognormal product distribution. From (5.5), the PDF of the product of gamma and lognormal RVs is then given by

$$P_Z(z) = \frac{\xi z^{M-1}}{(M-1)!\,\sigma_{(dB)}\sqrt{2\pi}} \int_0^{\infty} \frac{exp(-z/v)}{v^{(M+1)}}\, exp\left(\frac{-(\xi \log_e v - \mu_{(dB)})^2}{2\sigma_{(dB)}^2}\right) dv, \tag{5.6}$$

From (5.6) it can be noticed that the PDF of SNR does not exist in a closed-form.

5.1.2 SINR of MRC Receiver:

Based on the lognormal approximation of SNR, the SINR of an MRC receiver can also be approximated by a lognormal RV. Approximating the SINR by a lognormal RV is based on the two above mentioned approximating methods. The summation in the denominator of (5.2) involves a product of exponential and lognormal RVs. Since gamma RV is a sum of i.i.d. exponential RVs, substituting M = 1 in (5.6) gives the PDF of the product of exponential and lognormal RVs as

$$P_Z(z) = \frac{\xi}{\sigma_{(dB)}\sqrt{2\pi}} \int_0^\infty \frac{\exp(-z/v)}{v^2} \exp\left(\frac{-(\xi \log_e v - \mu_{(dB)})^2}{2\sigma_{(dB)}^2}\right) dv, \tag{5.7}$$

From (5.7), it is clear that the distribution of the product of these RVs also does not exist in a closed-form. However, like the gamma-lognormal product distribution, the exponential-lognormal product distribution can be approximated by another lognormal RV, W ~ Log-N(μ_a, σ_a^2).

In terms of the approximating lognormal RVs, the expression for the SINR of a single user from (5.2) can be written as

$$SINR_j^{mrc} \triangleq \frac{P_t Y}{P_t + 1}, \tag{5.8}$$

where Y ~ Log-N(μ_X, σ_X^2) is obtained by either the moment matching method or the MGF-based method and R ~ Log-N(μ_b, σ_b^2) is obtained as stated above. Multiplication of a lognormal RV by P_t adds $\xi \log_e P_t$ to the mean value of the associated Gaussian RV whereas the addition of 1 to the RV R in the denominator of (5.8) simply adds unity to the expected value of RV R.

5.2 Analysis of MMSE Receiver:

In MIMO wireless communication, an equalizer is needed which is a network that is used to recover a signal that suffers from Inter symbol Interference (ISI) and the BER characteristics is improved and a good SNR is maintained. A Minimum Mean Square Error (MMSE) estimator is a method which reduces the mean square error (MSE). MMSE equalizer does not completely eliminate ISI but minimizes the total power of the noise and ISI components in the output.

The detector matrix A for an MMSE receiver is given by $A = G(G^H G + \frac{1}{P_t} I_K)^{-1}$. The j_{th} column of A is given as

$$a_j = \frac{F g_j}{1 + g_j^H F g_j} \tag{5.9}$$

Where $F = (G_j G_j^H + \frac{1}{P_t} I_M)$ and G_j is the submatrix obtained after omitting the j_{th} column of G. Substituting (5.9) into (5.7), we get the SINR of j_{th} user as

$$SINR_j^{mmse} = \frac{1}{[(P_t G^H G + I_K)^{-1}]_{jj}} - 1. \tag{5.10}$$

5.3 CDM-Based Signal Detector:

The CDM optimizes one variable at a time while holding others fixed at their most recently updated values. Typically, the optimization coordinate is chosen cyclically. However, CDM is efficient when the subproblems can be solved quickly.

For a given $X_{-\mu} \triangleq [x_1, \dots, x_{\mu-1}, x_{\mu+1}, \dots, x_U]$, the optimal value of $x_\mu = A_\mu e^{j\theta_\mu}$ that minimizes $\|y - Hx\|^2$ is given by

$$A_\mu^\star = \frac{|\xi_\mu|}{\sum_{b=1}^{B} |H_{b\mu}|^2} \tag{5.11a}$$

$$\theta_\mu^\star = \arg\{\xi_\mu\}, \tag{5.11b}$$

Where

$$\xi_\mu \triangleq \sum_{b=1}^{B} H_{b\mu}^\star \left(y_b - \sum_{v=1, v\neq\mu}^{U} H_{bv} A_v e^{j\theta_v}\right). \tag{5.12}$$

To outline the problem concretely the optimal update problem can be written as

$$A_\mu^\star e^{j\theta_\mu^\star} = \arg\min \|y - Hx\|^2 \tag{5.13}$$

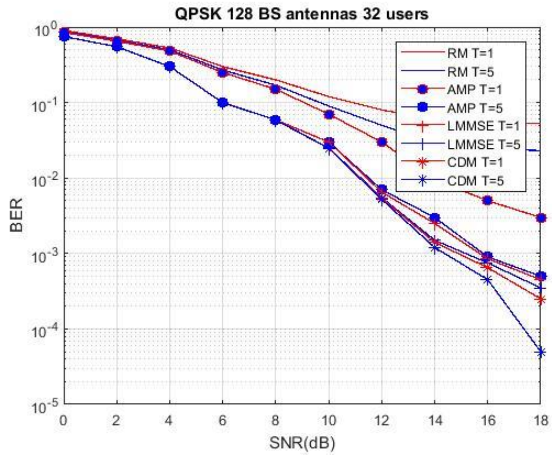
$$= arg\ min \sum_{b=1}^{B} \left| y_b - \sum_{v=1}^{U} H_{bv} A_v e^{j\theta_v} \right|^2. \tag{5.14}$$

CHAPTER-6

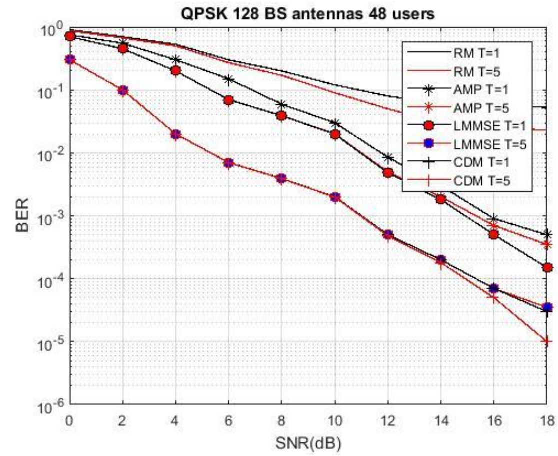
SIMULATION RESULTS AND PERFORMANCE ANALYSIS

In this section, the BER and complexity performance of the proposed CDM-based detector are evaluated through Monte Carlo simulations, where each entry of the channel matrix H is an independent circularly symmetric complex Gaussian random variable (i.e., $H_{b\mu} \sim \mathcal{N}_{\mathbb{C}}(0{,}1/B)$). The signal-to-noise ratio (SNR) is given by E_b/N_0, where E_b is the bit energy. For comparison, other approximate data detection methods for massive multi-user MIMO systems were also tested, including the RM-based detector [22], the AMP-based detector [28], and the classical LMMSE detector.

Figs. 6.1(a) and 6.1(b) illustrate the BER results as a function of SNR using QPSK modulation for antenna configuration $B \times U$ = 128×32 and $B \times U$ = 128×48. Here we consider two types of time durations or slots, say T=1 and T=5 for all the four techniques RM, AMP, LMMSE and CDM. These figures provide the following observations: First, for a fixed B, increasing U deteriorates the BER performance for these algorithms under the same SNR value. Second, the BER performance improves as the number of iterations increases for the RM assisted detector, the AMP-assisted detector, and the proposed CDM-based detector. When the iteration counts are the same, excluding the initial two iterations, the BER performance of the proposed CDM-based detector is superior to that of the RM-assisted detector and the AMP-assisted detector regardless of the antenna configuration employed. Thus, the proposed CDM-based detector requires less iteration to achieve the same BER performance as the RM-assisted detector and the AMP-assisted detector. For example, the BER performance of the proposed scheme with T = 3 was higher than that of the AMP-assisted detector with T = 5 [Fig. 6.1(a)]; the BER performance of the proposed scheme with T = 3 was higher than that of the RM-assisted detector with T = 4 [Fig. 6.2(b)]. This finding indicates that a faster convergence rate can be obtained for the proposed CDM data detection algorithm. Third, although the BER performances of both the RM-assisted detector and the AMP-assisted detector are similar to that of the LMMSE detector, the proposed CDM based detector outperforms the classical LMMSE detector for all the scenarios considered. This observation verifies the effectiveness of the proposed CDM-based detector.

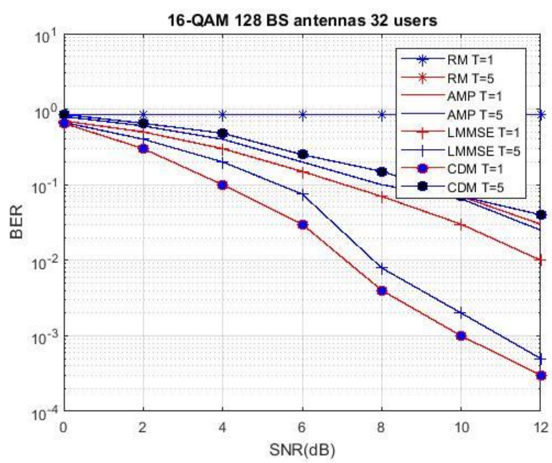


(a) 128 BS antennas and 32 users

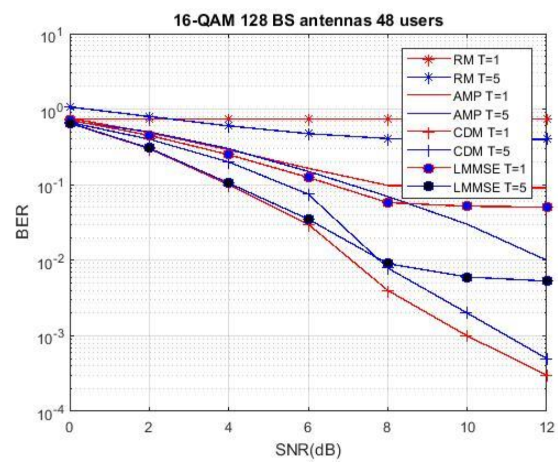


(b) 128 BS antennas and 48 users

Fig.6.1: BER versus SNR for (a) the 128 × 32 massive MIMO system with QPSK modulation and (b) the 128 × 48 massive MIMO system with QPSK modulation.

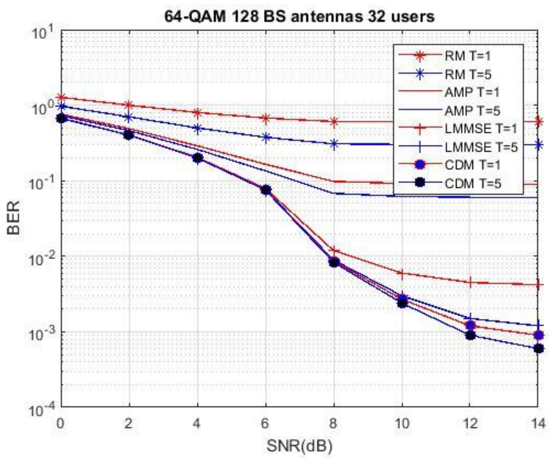


(a) 128 BS antennas and 32 users

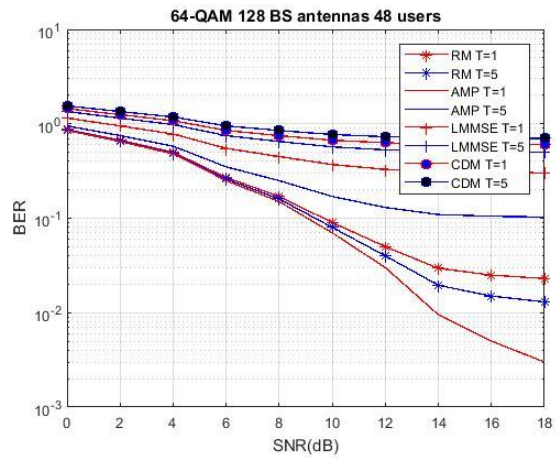


(b) 128 BS antennas and 48 users

Fig.6.2: BER versus SNR for (a) the 128 × 32 massive MIMO system with 16-QAM modulation and (b) the 128 × 48 massive MIMO system with 16-QAM modulation.



(a) 128 BS antennas and 32 users



(b) 128 BS antennas and 48 users

Fig.6.3: BER versus SNR for (a) the 128 × 32 massive MIMO system with 64-QAM modulation and (b) the 128 × 48 massive MIMO system with 64-QAM modulation.

Next, we examined the behavior of the proposed CDM-based detector for higher-order and non-constant amplitude modulations. Figs. 6.2 and 6.3 shows the BER displayed as a function of SNR for different antenna configurations with 16-QAM and 64-QAM modulation, respectively. The settings were identical to those in Fig. 6.1 except for the modulation scheme. Figs. 6.2 and 6.3 reveal similar performance trends to those exhibited in Fig. 6.1, which implies that most of the observations of Fig. 6.1 also hold true for these scenarios with 16-QAM and 64-QAM modulation schemes. However, because of the increase in the order of the modulation (the size of the problem), the RM-assisted detector, the AMP-assisted detector, and the proposed CDM-based detector require more iterations to obtain the desired results than do those in Fig. 6.1 under the same antenna configuration (Figs. 6.2 and 6.3).

From the below fig.6.4 we can observe the error performance comparison for correlated channel. Simulation results were obtained for i.i.d. frequency-flat Rayleigh fading MIMO channels. However, the performance of MIMO systems in realistic radio environments depends heavily on *spatial correlation*. Therefore, we investigated the effect of channel correlation on the performance of the test algorithms. On the basis of [30], the spatially correlated channel was modelled as

$$H_{sc} = \sqrt{R}H, \tag{6.1}$$

where $R \in \mathbb{R}^{B\times B}$ is the correlation matrix at the BS.

Fig.6.4 demonstrate the BER performances against SNR for a 128 × 48 *correlated* MIMO channel with QPSK modulation scheme with a spatial correlation coefficient ρ = 0.2. By increasing the channel correlation ρ, it causes slight performance degradation for the LMMSE algorithm. Although the proposed CDM-based algorithm requires more iterations to achieve convergence for spatially correlated channel environments, the BER performance of the proposed CDM-based detector is superior to (is the same as) that of the LMMSE detector for QPSK. Most importantly, the proposed CDM-based algorithm still has lower complexity than both the RM-based algorithm and the LMMSE scheme.

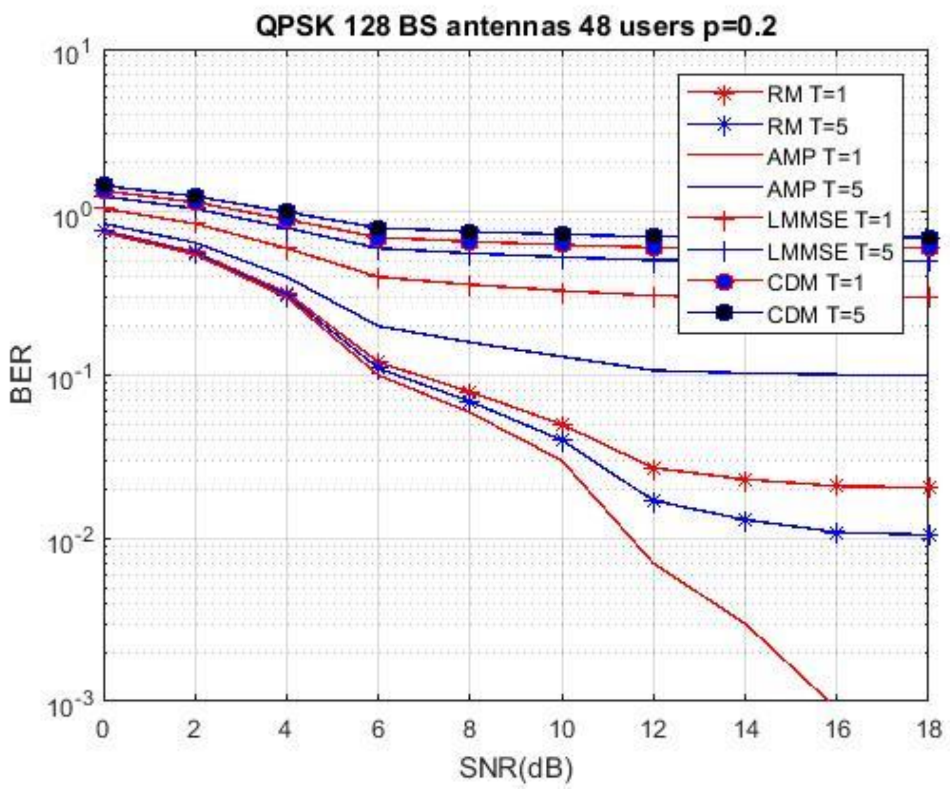


Fig.6.4: BER performances of QPSK modulation scheme for a 128 × 48 massive MIMO system with ρ = 0.2

Seeing how much of a performance gap exists between the proposed CDM-based detector and the ML detector is interesting. Therefore, here we compared the BER performance of the proposed CDM-based algorithm with that of the ML detection using the sphere decoding (SD) algorithm [33]. However, as reported in [34] and [35], the worst case and average computational complexity of the conventional SD algorithms still grows *exponentially* with U. In this case, the computational complexity required to perform SD for the above adopted system configurations (i.e., $B \times U = 128 \times 32$ and $B \times U = 128 \times 48$) is difficult to achieve. We can only reasonably perform SD for "appropriate" system configurations. Accordingly, the system configuration with $B \times U = 128 \times 16$ is selected for simulation in this subsection, as in [22] and [24]. Figs. 6.5–6.7 present the BER performances with $\rho = 0$ and $\rho = 0.3$ for LMMSE, CDM, and SD using QPSK, 16-QAM, and 64-QAM modulation, respectively.

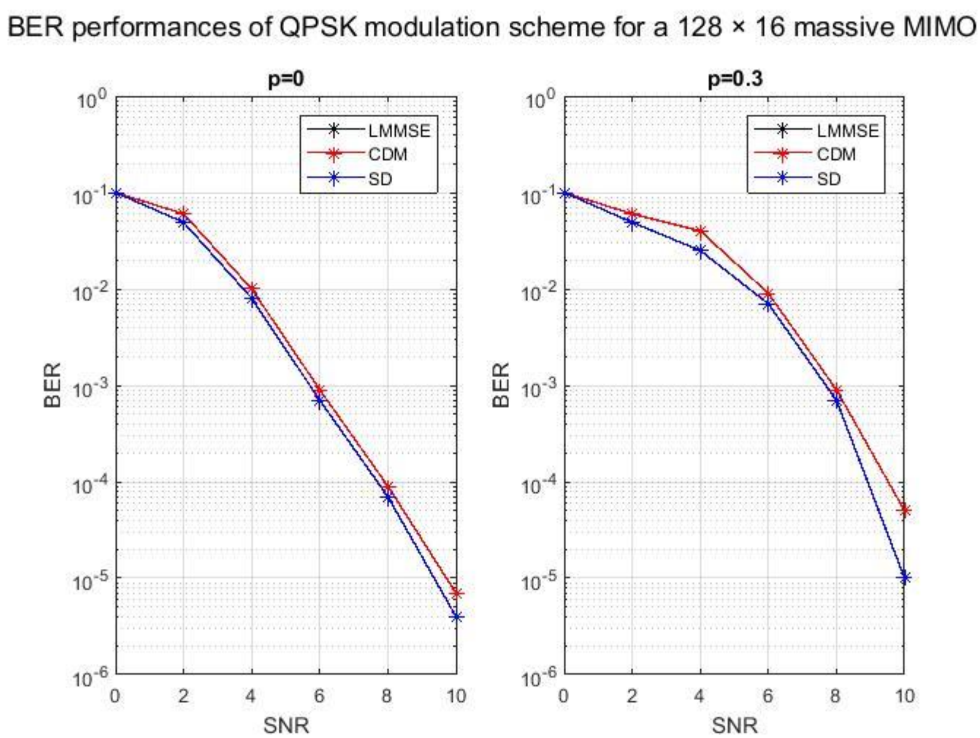


Fig.6.5: BER performances of QPSK modulation scheme for a 128 × 16 massive MIMO system with (a) $\rho = 0$ and (b) $\rho = 0.3$.

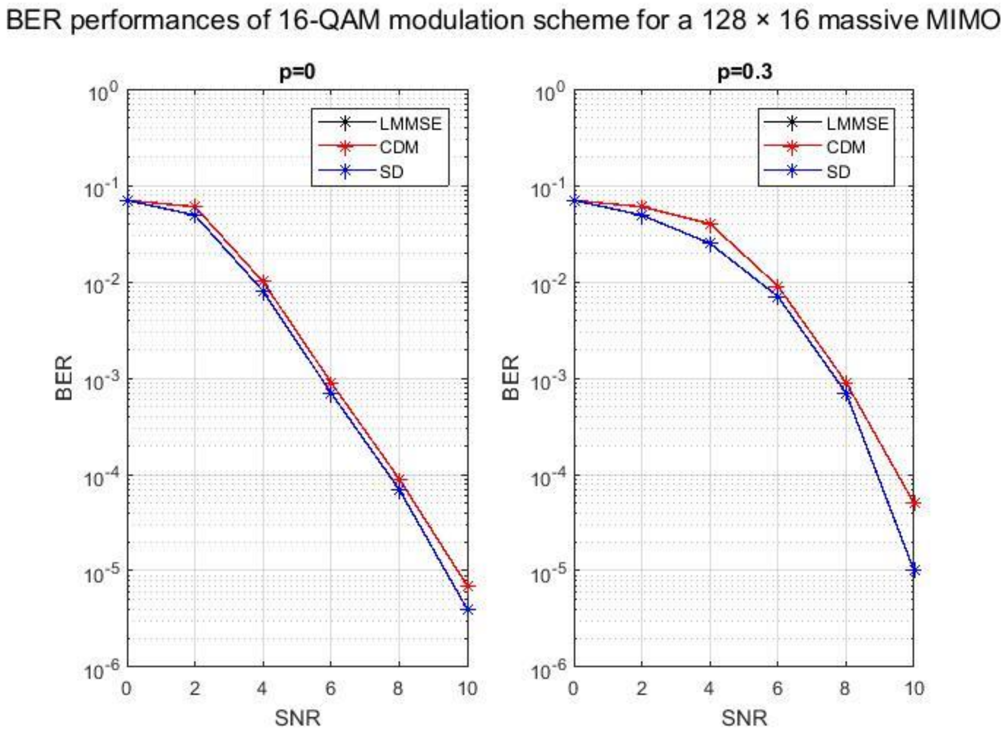


Fig.6.6: BER performances of 16-QAM modulation scheme for a 128 × 16 massive MIMO system with (a) ρ = 0 and (b) ρ = 0.3.

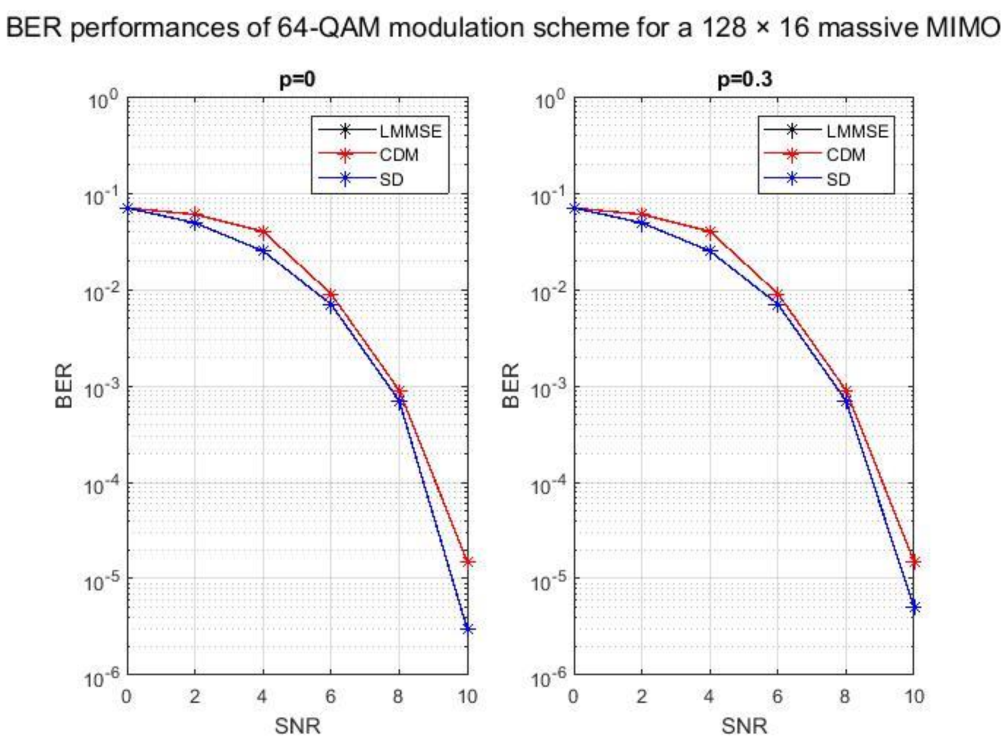


Fig.6.7: BER performances of 64-QAM modulation scheme for a 128 × 16 massive MIMO system with (a) ρ = 0 and (b) ρ = 0.3.

These results show that the proposed CDM-based algorithm provides the same or improved BER performance over the classical LMMSE algorithm. More importantly, we can also observe that the proposed CDM-based detector only suffers from a rather small performance loss as compared with the SD-based detector.

We examine in below Fig.6.8 the impact of noise variance for the CDM based detector having antenna configuration $B \times U$ = 128×32 massive MIMO system without spatial correlation using 16-QAM modulation. We can see that the BER performance of the CDM based detector is not affected by an inappropriate σ_ω^2 compared to the other data detection techniques.

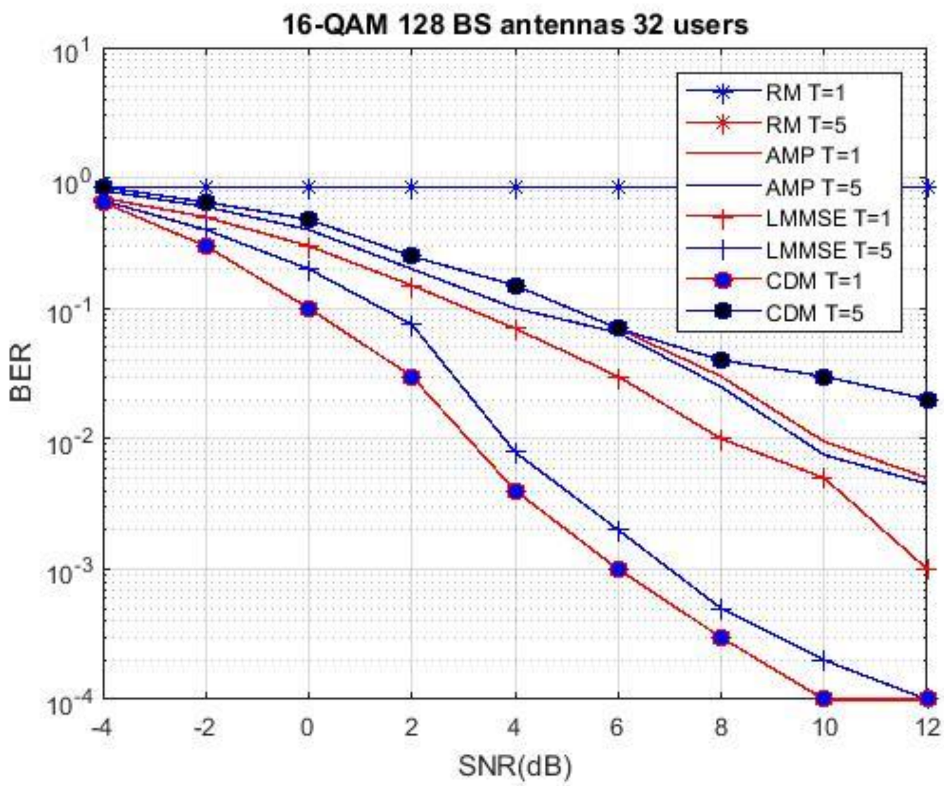


Fig.6.8: BER versus SNR for the 128 × 32 massive MIMO system with 16-QAM modulation, where the RM, AMP, LMMSE and CDM assisted detectors, adopts inappropriate σ_ω^2 drawn from a uniform distribution on the interval from $\mathcal{U}_a$ to $\mathcal{U}_b$.

Finally from the below Fig.6.9 we can observe the Total Training Power with respect to Mean Square Error behavior for different data detection methods. We can clearly analyze in the context of an MRC receiver the MSE parameter with respect to the total training power.

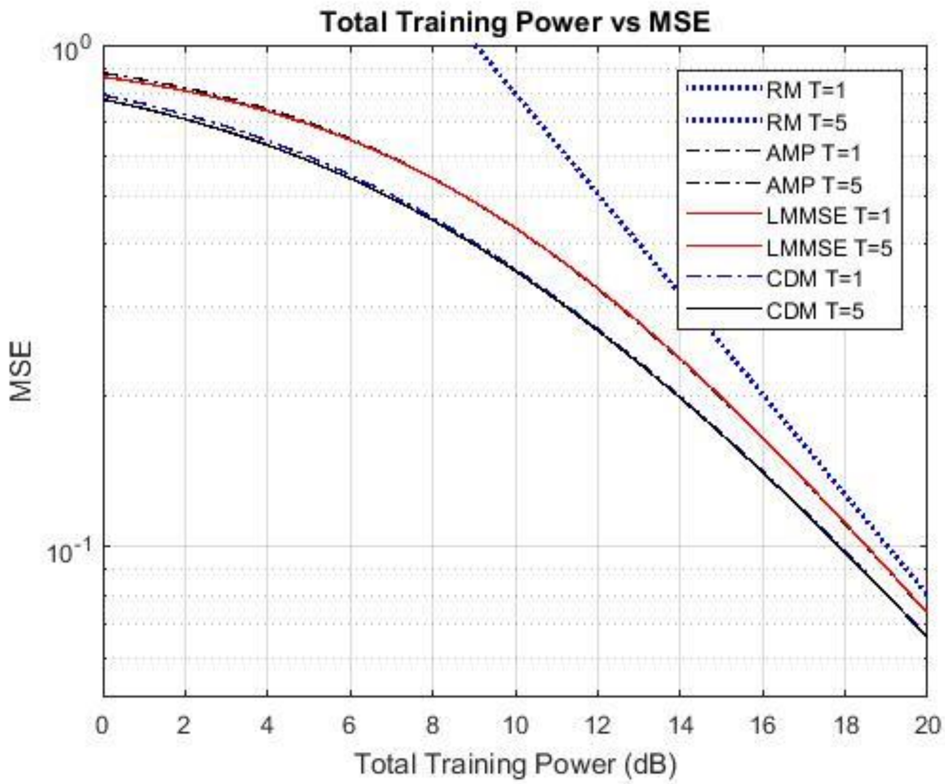


Fig.6.9: Total Training Power versus MSE for massive MIMO system in comparison of different methods RM, AMP, LMMSE and CDM.

So with the help of MRC combined with CDM technique, the proposed system results better MSE performance compared to the remaining methods. This shows the effectiveness and efficiency of the proposed method.

Pseudo code:

```
nbrOfMonteCarloRealizations = 1;
T = 1;
T = 5;
Nt = 8;
Nr = 8;
P = 0:0.1:0.3;
P = 0:1:20; %In decibel scale
totalTrainingPower = 10.^(P/10);
option = optimset('Display','off','TolFun',1e-7,'TolCon',1e-7,'Algorithm','interior-point');
SNR = 0:2:18;
average_BER_MMSE_estimator_RM = zeros(length(totalTrainingPower),T,2);
average_BER_MMSE_estimator_AMP = zeros(length(totalTrainingPower),T,2);
average_BER_CDM_estimator = zeros(length(totalTrainingPower),T,2);
average_BER_LMMSE_estimator = zeros(length(totalTrainingPower),T,2);
average_BER_twosided_estimator = zeros(length(totalTrainingPower),T,2);

for statisticsIndex = 1:T
    V = abs(randn(Nr,Nt)+1i*randn(Nr,Nt)).^2;
    V = Nt*Nr*V/sum(V(:));
    R = diag(V(:));
    R_T = diag(sum(V,1));
    R_R = diag(sum(V,2));
    trainingpower_MMSE_RM = zeros(Nt,length(totalTrainingPower));

    for k = 1:length(totalTrainingPower)
        trainingpower_initial = totalTrainingPower(k)*ones(Nt,1)/Nt;
        trainingpower_MMSE_RM(:,k) = fmincon(@(q)
functionBERmatrix(R,q,Nr),trainingpower_initial,ones(1,Nt),totalTrainingPower(k),[],[],zeros(N
t,1),totalTrainingPower(k)*ones(Nt,1),[],option);
```

```
    end

    [eigenvalues_sorted,permutationorder] = sort(diag(R_T),'descend');
    [~,inversePermutation] = sort(permutationorder);

    q_MMSE_AMP = zeros(Nt,length(totalTrainingPower));
    for k = 1:length(totalTrainingPower)
        alpha_candidates =
(totalTrainingPower(k)+cumsum(1./eigenvalues_sorted(1:Nt,1)))./(1:Nt)';
        RMIndex = find(alpha_candidates-1./eigenvalues_sorted(1:Nt,1)>0 & alpha_candidates-
[1./eigenvalues_sorted(2:end,1); Inf]<0);
        q_MMSE_AMP(:,k) = max([alpha_candidates(RMIndex)-1./eigenvalues_sorted(1:Nt,1)
zeros(Nt,1)],[],2);
    end

    q_MMSE_AMP = q_MMSE_AMP(inversePermutation,:);
    q_uniform = (ones(Nt,1)/Nt)*totalTrainingPower;

    vecH_realizations =
sqrtm(R)*(randn(Nt*Nr,nbrOfMonteCarloRealizations)+1i*randn(Nt*Nr,nbrOfMonteCarloReali
zations) ) / sqrt(2);
    vecN_realizations =
(randn(Nt*Nr,nbrOfMonteCarloRealizations)+1i*randn(Nt*Nr,nbrOfMonteCarloRealizations) )
/ sqrt(2);

    for k = 1:length(totalTrainingPower)

        P_tilde = kron(diag(sqrt(trainingpower_MMSE_RM(:,k))),eye(Nr));

        average_BER_MMSE_estimator_RM(k,statisticsIndex,1) =
trace(R - (R*P_tilde'/(P_tilde*R*P_tilde' + eye(length(R))))*P_tilde*R);
```

```
H_hat=(R*P_tilde'/(P_tilde*R*P_tilde'+eye(length(R))))*(P_tilde*vecH_realizations+vecN_real
izations);
        average_BER_MMSE_estimator_RM(k,statisticsIndex,2) =
mean( sum(abs(vecH_realizations - H_hat).^2,1) );

        P_tilde = kron(diag(sqrt(q_MMSE_AMP(:,k))),eye(Nr));

        average_BER_MMSE_estimator_AMP(k,statisticsIndex,1) =
trace(R - (R*P_tilde'/(P_tilde*R*P_tilde' + eye(length(R))))*P_tilde*R);

        H_hat = (R*P_tilde'/(P_tilde*R*P_tilde'+eye(length(R)))) * (P_tilde*vecH_realizations +
vecN_realizations);
        average_BER_MMSE_estimator_AMP(k,statisticsIndex,2) =
mean(sum(abs(vecH_realizations - H_hat).^2,1) );

        P_training = diag(sqrt(q_uniform(:,k)));
        P_tilde = kron(transpose(P_training),eye(Nr));
        P_tilde_pseudoInverse = kron((P_training'/(P_training*P_training'))',eye(Nr));

        average_BER_CDM_estimator(k,statisticsIndex,1) = Nt^2*Nr/totalTrainingPower(k);

        H_hat = P_tilde_pseudoInverse'*(P_tilde*vecH_realizations + vecN_realizations);
        average_BER_CDM_estimator(k,statisticsIndex,2) =
mean( sum(abs(vecH_realizations - H_hat).^2,1) );

        P_training = diag(sqrt(q_MMSE_AMP(:,k)));
        P_tilde = kron(P_training,eye(Nr));
        average_BER_LMMSE_estimator(k,statisticsIndex,1) =
trace(inv(inv(R_T)+P_training*P_training'/Nr));
```

```
        Ao = (P_training'*R_T*P_training + Nr*eye(Nt))\P_training'*R_T;
        H_hat = kron(transpose(Ao),eye(Nr))*(P_tilde*vecH_realizations + vecN_realizations);
        average_BER_LMMSE_estimator(k,statisticsIndex,2) =
mean( sum(abs(vecH_realizations - H_hat).^2,1) );

        P_training = diag(sqrt(q_uniform(:,k)));
        P_tilde = kron(P_training,eye(Nr));
        R_calE = sum(1./q_uniform(:,k))*eye(Nr);

        average_BER_twosided_estimator(k,statisticsIndex,1) =
trace(R_R-(R_R/(R_R+R_calE))*R_R);

        C1 = inv(P_training);
        C2bar = R_R/(R_R+R_calE);
        H_hat = kron(transpose(C1),C2bar)*(P_tilde*vecH_realizations + vecN_realizations);
        average_BER_twosided_estimator(k,statisticsIndex,2) =
mean( sum(abs(vecH_realizations - H_hat).^2,1) );
        BER=ber(SNR);
    end

end
```

Chapter-7

CONCLUSION AND FUTURE SCOPE

7.1 Conclusion

This project proposes an energy efficient and low complexity data detection method for uplink multi-user massive MIMO systems. The optimal and suboptimal data detection algorithms like linear minimum mean square error, approximate message passing, etc., may not provide satisfactory bit error rate (BER) performance. Here, a maximum ratio combining (MRC) receiver is considered for a very large scale multi-user MIMO system under a composite-fading environment and combined it with the coordinate descent method (CDM) technique. The CDM is taken into consideration because of its low complexity and better performance compared to other conventional techniques. The simulation results show that the proposed system results better MSE or BER performance. The comparison results analyzing total training power with respect to MSE for the different methods RM, AMP, LMMSE and CDM shows the energy efficiency of the proposed system Thus this new approach is substantially energy efficient and low complex.

7.2 Future Scope

- Extending the devised approach to a multi-cell scenario.
- The performance bounds of the Massive MIMO detectors in spatially correlated channels are not known. A rigorous investigation is required to quantify the performance bounds which can be used as a benchmark instead of the maximum likelihood detector whose performance cannot be simulated for Massive MIMO systems.
- Further investigations are required to reduce the complexity, in terms of execution time by exploiting probable parallelization of the algorithm.

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APPENDIX - A

PUBLICATION DETAILS

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APPENDIX – B

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