

Precoded Large Scale Multi-User-MIMO System Using Likelihood Ascent Search for Signal Detection

Kalapraveen Bagadi¹, Chinthaginjala V. Ravikumar¹, Mohammad Alibakhshikenari², Nagaraj Challa³, Anbazhagan Rajesh⁴, Sonia Aïssa⁵, Iyad Dayoub^{6,7}, Francisco Falcone^{8,9}, and Ernesto Limiti¹⁰

¹School of Electronics Engineering, Vellore Institute of Technology (VIT), Vellore, India, ²Department of Signal Theory and Communications, Universidad Carlos III de Madrid, Leganés, Madrid, Spain, ³Department of Electronics and Communication Engineering, Bapatla Engineering College, Bapatla, India, ⁴SASTRA University, Thanjavur, India, ⁵Institut National de la Recherche Scientifique (INRS), Montreal, QC, Canada, ⁶Université Polytechnique Hauts-de-France, CNRS, University of Lille, ISEN, Centrale Lille, UMR 8520, Institut d'Électronique de Microélectronique et de Nanotechnologie (IEMN), Valenciennes, France, ⁷INSA Hauts de France, Valenciennes, France, ⁸Department of Electric, Electronic and Communication Engineering, Institute of Smart Cities, Public University of Navarre, Pamplona, Spain, ⁹School of Engineering and Sciences, Tecnológico de Monterrey, Monterrey, Mexico, ¹⁰Electronics Engineering Department, University of Rome "Tor Vergata", Rome, Italy

Key Points:

- An Lenstra-Lovasz (LLL)-based Lattice Reduction (LR) aided likelihood ascent search (LAS) detector for large-scale multi-user multiple input multiple output systems is suggested
- This work reduces the performance-complexity gap while also mitigating inter antenna interference and multi-user interference
- The suggested LLL-based LR-LAS approaches achieve maximum likelihood (ML) performance with a significant complexity gain over ML detector than traditional ones

Correspondence to:

C. V. Ravikumar and M. Alibakhshikenari,
cvrkvit@gmail.com;
mohammad.alibakhshikenari@uc3m.es

Citation:

Bagadi, K., Ravikumar, C. V., Alibakhshikenari, M., Challa, N., Rajesh, A., Aïssa, S., et al. (2022). Precoded large scale multi-user-MIMO system using likelihood ascent search for signal detection. *Radio Science*, 57, e2022RS007573. <https://doi.org/10.1029/2022RS007573>

Received 2 AUG 2022
Accepted 17 NOV 2022

Author Contributions:

Conceptualization: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Anbazhagan Rajesh
Data curation: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Anbazhagan Rajesh
Formal analysis: Kalapraveen Bagadi
Investigation: Sonia Aïssa, Iyad Dayoub, Francisco Falcone
Methodology: Kalapraveen Bagadi, Mohammad Alibakhshikenari, Nagaraj Challa, Francisco Falcone

© 2022. The Authors.

This is an open access article under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

Abstract Multiple antennas at each user equipment (UE) and/or thousands of antennas at the base station (BS) comprise the extremely spectrum efficient large scale multi-user multiple input multiple output system (BS). Due to space constraints, the closely spaced numerous antennas at each UE may cause inter antenna interference (IAI). Furthermore, when one UE comes into contact with another UE in the same cellular network, multi-user interference (MUI) may be introduced to the received signal. To mitigate IAI, efficient precoding pre-coding is necessary at each UE, and the MUI present at the BS can be canceled by efficient Multi-user Detection (MUD) techniques. The majority of earlier literature deal with one or more of these interferences. This paper implements a joint pre-coding and MUD, Lenstra-Lovasz (LLL) based Lattice Reduction (LR) assisted likelihood ascent search (LAS) (LLL-LR-LAS), to mitigate IAI and MUI simultaneously LLL-based LR pre-coding mitigates IAI at each UE, and the LAS algorithm is a neighborhood search-based MUD that cancels BS MUI. The proposed approaches' performance was evaluated using Bit Error Rate analysis, and their complexity were determined using multiplication and addition.

1. Introduction

Large-scale space division multiple access or massive multi-input multi-output (MIMO) is now widely recognized as a crucial enabler for the realistic implementation of 5G wireless communication networks (L. Miller & J. Lee, 1998; A. J. Viterbi, 1995). The transmitter and/or receiver terminals of the huge MIMO system use a high number of antennas as their primary design concept (K. P. Bagadi & S. Das, 2013). The spectrum efficiency, channel capacity gain, and multiplexing gain can all be improved by strategically placing many antennas (K. P. Bagadi & S. Das, 2014). The point-to-point MIMO communication system was well-explained in the literature (K. P. Bagadi & S. Das, 2013). Researchers have recently moved their focus to large-scale multi-user MIMO (MU-MIMO) systems in order to address the enormous demand for high data rates (K. Bagadi & S. Das, 2014). MU-MIMO is a multi-data transmission system that allows the base station (BS) to deploy a huge array of antennas (fewer than hundreds) while the user equipment (UE) only uses a small number of antennas (K. P. Bagadi et al., 2016). A key advantage of the MU-MIMO system over the standard MIMO approach is its higher spectral efficiency and higher power consumption (S. B. Weinstein & P. M. Ebert, 1971).

Large-scale implementations in the real world problems include computational complexity, acquisition of Channel State Information (CSI), and design of pre-coding and detection techniques for MU-MIMO systems (R. Prasad, 2004). Interference degrades wireless communication system performance, as is well-known (R. Prasad & S. Hara, 1997). Many antennas at the transmitter and/or receiver end of the MU-MIMO system create inter antenna interference (IAI) at the UE and multi-user interference (MUI) at the BS (McCormick and Al-Susa, 2002). Figure 1 depicts a huge MU-MIMO system with IAI at a UE and MUI at the BS, as shown in the figure. IAI occurs when the distance between each UE antenna is smaller than the typical half-wavelength rule. It is a problem in wireless communications. At the receiver, the MUI is generated (Kalapraveen & C. V. Ravikumar, 2016). MUI can occur as a result of impulse responses at each UE becoming almost identical in close proximity to one

Resources: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Nagaraj Challa, Anbazhagan Rajesh
Software: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Nagaraj Challa, Anbazhagan Rajesh
Validation: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Mohammad Alibakhshikenari, Nagaraj Challa, Anbazhagan Rajesh, Sonia Aïssa, Iyad Dayoub, Francisco Falcone, Ernesto Limiti
Visualization: Chinthaginjala V. Ravikumar, Mohammad Alibakhshikenari, Nagaraj Challa, Anbazhagan Rajesh, Sonia Aïssa, Iyad Dayoub, Ernesto Limiti
Writing – original draft: Kalapraveen Bagadi, Chinthaginjala V. Ravikumar, Nagaraj Challa
Writing – review & editing: Mohammad Alibakhshikenari, Sonia Aïssa, Iyad Dayoub, Francisco Falcone, Ernesto Limiti

another. The channel impulse response serves as a spatial signature for each UE in MU-MIMO systems. Most of the aforementioned research studies only deal with one or the other of IAI or MUI, but the present work focuses on both and achieves near-optimal performance with minimal computing complexity, which is a major difference. Pre-coding techniques are needed to reduce this IAI and improve signal data transmission accuracy (J. G. Proakis, 1995). Both IAI and computational complexities are reduced as a result of pre-coding approaches like this. One of the best pre-coders for bit error rate (BER) performance, ML (R. Steele & L. Hanzo, 1999) outperforms the rest. Even with a limited number of antennas, the computational cost is prohibitive. Because of their lower complexity structure, linear pre-coders such as zero-forcing (ZF) (S. Verdu, 1998) and minimum mean square error (MMSE) (Y. Yan & M. Ma, 2015) are more appealing. However, these pre-coding systems require a lot of transmit power and perform poorly, especially when the channel matrix is bad. Vector perturbation is a non-linear pre-coding system (K. Bagadi et al., 2022) that addresses the closest lattice point problem using the sphere encoding technique. It achieves near-optimal performance but has non-deterministic polynomial time complexity. Tomlinson-Harashima Pre-coding is another non-linear pre-coding technique that is primarily recommended for suppressing inter-symbol interference (V. Erceg et al., 2001). However, the THP scheme's practical implementation is unsuitable for big MU-MIMO systems. Traditional pre-coding solutions clearly suffer from a performance-complexity trade-off. To address this issue, a Lattice Reduction (LR) scheme was implemented (J. C. Patra et al., 1999). LR is primarily based on an orthogonal decomposition of a channel basis vector, which allows IAI at the UE to be eliminated. Pre-coding in wireless MIMO communication systems is made a lot easier with LR, a powerful metaheuristic approach. Using the LR technique, the original MU-MIMO channel matrix is changed into a better conditioned channel matrix (i.e., it provides a nearly orthogonal and shorter channel basis vector in the same lattice), and the encoding may be conducted with much more confidence. The LR pre-coding, unlike sphere decoding, does not suffer from the problem of shape.

As a result, the system is able to run at a near-optimal level with fewer computations. As a powerful and well-known reduction technique, LLL evaluates the new equivalent channel matrix with an average polynomial time complexity (M. D. Imaudin et al., 2020; C. V. Ravikumar & K. P Bagadi, 2016a, 2016b, 2017a, 2017b, 2017c; C. V. Ravikumar & K. C. Saranya, 2016a, 2016b) among several LR algorithms. However, the LR pre-coding approach requires that the CSI is known at the transmitter. For the construction of LR-assisted linear detection techniques, most recent literature has focused on advanced LR algorithms (Jayaprabath et al., 2019; C. V. Ravikumar & P. Venugopal, 2018). To the best of the author's knowledge, large-scale LR assisted MIMO pre-coding breakthroughs are yet possible. To eliminate channel correlation and IAI at the end user, LLL is the most feasible and often used LR method that transforms a non-orthogonal channel matrix into nearly orthogonal channel basis vectors. Each user's MIMO channel matrix is turned into nearly orthogonal channel basis vectors by applying LLL prior to LR-MIMO, which allows the system to achieve complete diversity gain with feasible complexity.

The MUI present at the receiver terminal is mitigated by using Multi-User Detection (MUD) scheme. Selection of efficient MUD scheme is a key challenge for large MU-MIMO systems. Various signal detection algorithms have been reported in the literature to address this issue (N. R.Challa & K. Bagadi, 2020; Jitish et al., 2020; C. V. Ravikumar & K. C. Saranya, 2016a, 2016b). Among all, Maximum Likelihood Detection/Maximum Likelihood Detector (MLD) achieves optimal performance, due to its global search strategy. However, it suffers from exponential time detection complexity even for small MIMO structure and higher order constellation schemes (C. V.Ravi Kumar & B. Kalapraveen, 2019). In order to design a low complexity detection algorithm, a local search-based detection algorithm can be considered as better alternative as they achieve near-optimal BER performance with considerable time detection complexity. The Likelihood Ascent Search (LAS) algorithm is one such search-based strategy (N. R.Challa & K. Bagadi, 2021; C.V. Ravikumar & K. P Bagadi, 2017a, 2017b, 2017c). LAS is a search algorithm that iterates through a neighborhood in order to find the best solution.

For as long as the ML cost increases, the LAS algorithm searches for the optimal solution while altering its immediate surroundings. The LAS algorithm's key strength is its basic structure and its ability to search for information within a certain geographic area. Because of this, detection takes a lot longer, but the BER is also improved. A high-order modulation method and huge MIMO structures are unquestionably supported by LAS. A considerable performance-complexity trade-off is achieved in this study by proposing an advanced and effective interference mitigation strategy for the uplink scenario of massive MIMO systems. The initial vector of the LAS detector is the LLL solution vector preceding the LR pre-coder, which performs the local neighborhood search operation until it reaches ML saturation. This is the proposed approach. Consequently, the suggested method achieves near-optimal BER performance with manageable complexity. It's as follows throughout the rest of the paper: Section 2 studies

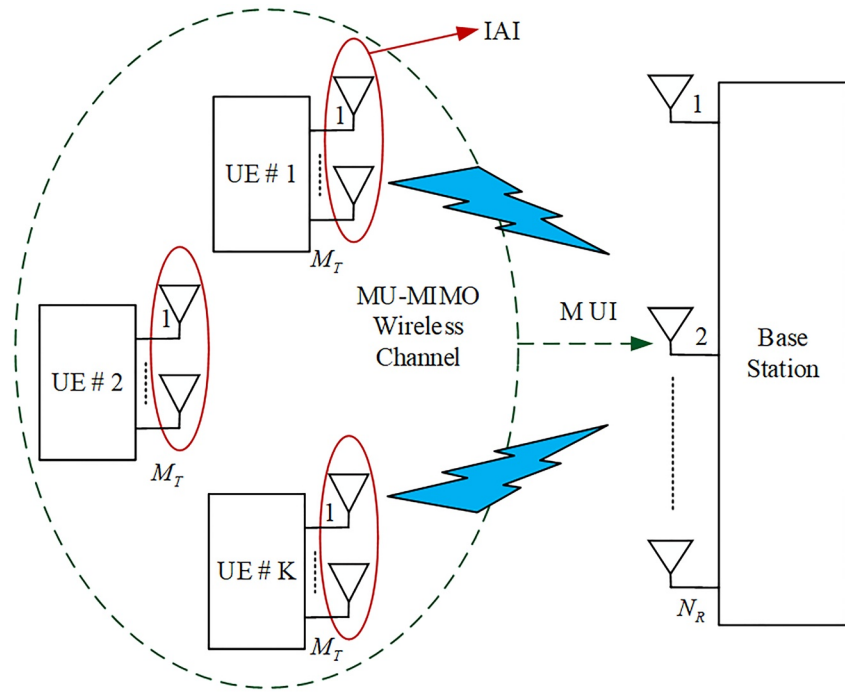


Figure 1. Massive Multi-User Multiple Input Multiple Output system representing Inter Antenna Interference at User Equipment and Multi-User Interference at base station.

the MU-MIMO system's mathematical model. The LR pre-coding with LLL technique is shown in Section 3 of the paper. LAS-based linear detectors and traditional MUD methods are discussed in Section 4 of this document. LR assisted LAS detector design is discussed in Section 5. Section 6 examines the simulation results and complexity analysis in depth, and Section 7 concludes with a summary.

2. Methods and Materials

Figure 2 shows a block diagram of the proposed MU-MIMO uplink system with LR pre-coding, which is shown. A large-scale MU-MIMO system's uplink consists of K independent UEs, each with M_T transmitting antennas, as described in this work. To sum it all up, there are N_T transmitting antennas where $N_T = K \times M_T$. On a single channel, all UTs communicate with a BS that has N_R receiving antennas. A big MU-MIMO system is defined as one that has a large number of antennas at both the transmitter and receiver. The BS receiver is able to gain all of the CSI, but the k th UE is able to obtain its own CSI that the channel between the BS and the k th $\mathbf{d}_k = [d_{1k}, d_{2k}, \dots, d_{M_T k}]^T$ UE can be obtained. It is, however, unknown to the k th UE what other UEs' CSI is. Furthermore, we assumed that all UEs are unconnected and do not work together. The signal mapper first modulates the k th UE bit vector, $\mathbf{b}_k^c = [b_{1k}, b_{2k}, \dots, b_{M_T k}]^T$ where $k = 1, 2, \dots, K$, to construct an uncoded complex data symbol vector. Because of the LR pre-coding approach for mitigating IAI, these un-coded vectors are encoded as $\mathbf{x}_k^c = [x_{1k}^c, x_{2k}^c, \dots, x_{M_T k}^c]^T$. The k th UE's complex pre-coded signal vector is sent through a user-specific complex channel vector by M_T transmitting antennas. As an example, let's say the channel coefficient matrix is composed of two M_T antennas and two BS antennas.

$$\mathbf{H}_k^c = \begin{bmatrix} h_{11}^k & h_{12}^k & \dots & h_{1M_T}^k \\ h_{21}^k & h_{22}^k & \dots & h_{2M_T}^k \\ \vdots & \vdots & \ddots & \vdots \\ h_{N_R 1}^k & h_{N_R 2}^k & \dots & h_{N_R M_T}^k \end{bmatrix} \quad (1)$$

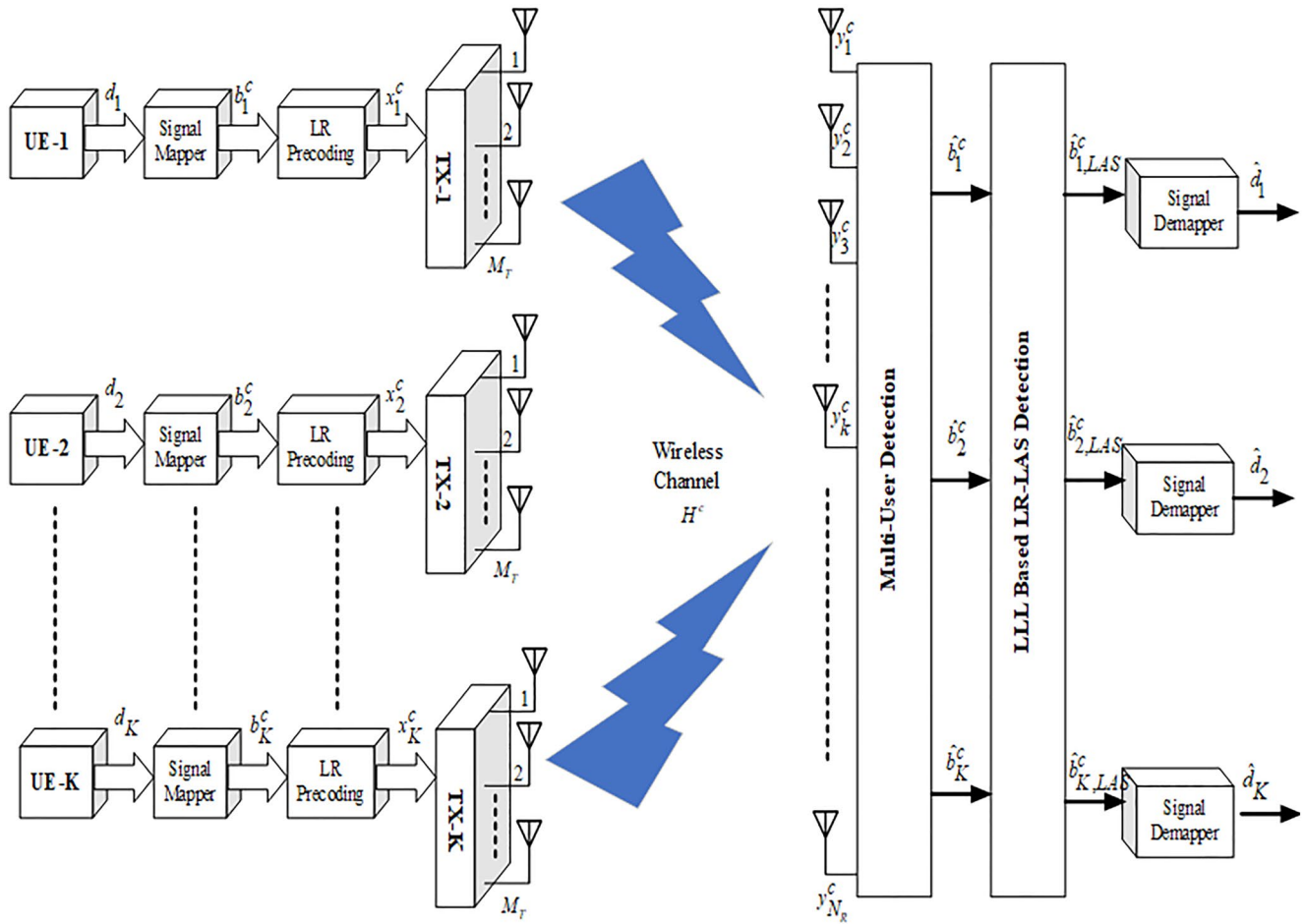


Figure 2. Block diagram of a proposed Lattice Reduction pre-coded Likelihood Ascent Search detector.

K simultaneous UEs' ($N_R \times 1$) dimensional complex signal vector is analytically described using the supplied channel matrix.

$$\mathbf{y}^c = \sum_{k=1}^K \mathbf{H}_k^c \mathbf{x}_k^c + \mathbf{n}^c \quad (2)$$

where $\mathbf{n}^c = [n_1^c, n_2^c, \dots, n_{N_R}^c]^T$ is the Independent Identical distribution Additive White Gaussian Noise (IID-AWGN) with the covariance matrix and a mean of zero. The complex MIMO system is modeled as an identical real-valued system for notational simplicity.

$$\mathbf{y} = \sum_{k=1}^K \mathbf{H}_k \mathbf{x}_k + \mathbf{n} \quad (3)$$

Where

$$\mathbf{x}_k = \left[\Re(\mathbf{x}_k^c)^T \quad \Im(\mathbf{x}_k^c)^T \right]^T_{(2M_T \times 1)} \quad \mathbf{y} = \left[\Re(\mathbf{y}^c)^T \quad \Im(\mathbf{y}^c)^T \right]^T_{(2N_R \times 1)}$$

$$\mathbf{n} = \left[\Re(\mathbf{n}^c)^T \quad \Im(\mathbf{n}^c)^T \right]^T_{(2N_R \times 1)}$$

$$\mathbf{H}_k = \begin{bmatrix} \Re(\mathbf{H}_k^c) & -\Im(\mathbf{H}_k^c) \\ \Im(\mathbf{H}_k^c) & \Re(\mathbf{H}_k^c) \end{bmatrix}_{(2N_R \times 2M_T)}$$

at this juncture, $\Im(\cdot)$ and $\Re(\cdot)$ components that are both real and fictitious

3. LLL Based LRPre-Coding Scheme

The main intension of performing the pre-coding scheme at a UE is to mitigate the IAI and improves the system performance. Several conventional pre-coding schemes have been discussed in literature (Buzzi & D'Andrea, 2018; Guo et al., 2021; Hong et al., 2020; Kibona et al., 2021). However, they are suffer from huge trade-off gap. Schemes that use linear regression to balance the performance-complexity trade-off have been developed. Pre-processing algorithm LR has recently received a lot of attention. Near-optimal performance can be achieved with little computing cost using LR. LR pre-coding, on the other hand, necessitates that each UE have CSI data. The original MIMO channel vector is turned into an analogous nearly orthogonal channel basis vector via LR pre-coding (better-conditioned). This collection of N-dimensional vectors (denoted by) is called a lattice. As the name implies, the lattice basis set of basis vectors can be used to characterize a real-valued channel matrix. As defined by the dictionary, a lattice is

$$L(\mathbf{H}_k) = L(\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_{M_T}) = \mathbf{H}_k \mathbf{x}_k \quad (4)$$

However, the same lattice is also traversed by the $(2N_R \times 2M_T)$ dimensional matrix $\tilde{\mathbf{H}}_k$, which is obtained by applying some basic column operation to the channel matrix \mathbf{H}_k . Let, \mathbf{T} be a $(2M_T \times 2M_T)$ dimensional unimodular matrix ($\det|\mathbf{T}| = \pm 1$), then the matrix $\tilde{\mathbf{H}}_k = \mathbf{H}_k \mathbf{T}_k$, generates same lattice as \mathbf{H}_k , that is,

$$L(\tilde{\mathbf{H}}_k) = L(\mathbf{H}_k) \quad (5)$$

The primary purpose of the LR technique is to transform a given channel matrix \mathbf{H}_k into a new basis, with the smallest Euclidean distance vector or, equivalently, with roughly orthogonal basis vectors. These roughly orthogonal columns of channel matrix mitigate IAI present at a UE.

$$\tilde{\mathbf{H}}_k = \mathbf{H}_k \mathbf{T}_k \quad (6)$$

At the receiver terminal, the real valued LR pre-coded signal vector is given as

$$\mathbf{y} = \sum_{k=1}^K \mathbf{H}_k (\mathbf{T}_k \mathbf{b}_k) + \mathbf{n} \quad (7)$$

From Equations 6 and 7 we have

$$\mathbf{y} = \sum_{k=1}^K \mathbf{H}_k \mathbf{T}_k \mathbf{T}_k^{-1} \mathbf{T}_k \mathbf{b}_k + \mathbf{n} \quad (8)$$

$$\mathbf{y} = \sum_{k=1}^K \tilde{\mathbf{H}}_k \mathbf{b}_k + \mathbf{n} \quad (9)$$

The pre-coding is performed with respect to the new channel matrix, which is a nearly orthogonal channel matrix.

4. Massive Multiuser Systems Multiple Inputs Multiple Outputs

In the huge MU-MIMO system, each user device performs Lattice Reduction pre-coding to reduce interference from other antenna terminals installed in the same user device. In spite of this, MU-MIMO is still plagued by interference from other transmitting UEs in the same wireless mesh network. Multi-user interference is the name given to this type of disturbance (MUI). Effective Multiuser detection techniques can help control this MUI. It is the primary goal of the Multiuser detection schemes technology to delete the interference from the

nearby undesired UE in order to reconstruct the intended UE transmitted signal vector from the received signal vector.

4.1. Zero Forcing Detector

Spatial interference is an issue with large-scale MU-MIMO systems because of their nearby antennas. An orthogonal subspace vector is projected onto the received signal to cancel out this interference. Using Moore-Penrose pseudo inverse of the channel matrix, the ZF detector performs a linear transformation at the receiver. The interference is successfully reduced by the ZF detector. In addition, it suffers from noise amplification, particularly in the case of a very large antenna array. For large MIMO structures, noise amplification approaches infinity due to random matrix theory (N. R. Challa & Bagadi, 2021, M. D. Imaudin et al., 2020, L. Miller & Lee, 1998).

4.2. Maximum Likelihood Detector

It is the primary goal of the signal detection system, which minimizes the Euclidean cost to retrieve the broadcast signal from the received signal vector, to do so. It is an optimum detector, the MLD, which looks at every single send signal and generates the best possible solution $b \in A^{2N_T}$. vectors have been mathematically characterized as

$$\hat{b}_{ML} = \arg \min_{b \in A^{2N_T}} \|y - Hb\|^2 \quad (10)$$

4.3. Linear Detectors Using Lattice Reduction

It is the channel matrix realization that has an effect on the linear detector's performance. For example, if the channel matrix is orthogonal, the ZF detector will perform optimally. Noise amplification is a problem, however. Receiver-side MMSE-based detectors reduce noise amplification by filtering it out. The linear detector is applied to the receiver side of the LR pre-coder in order to obtain an orthogonal channel matrix. These linear detectors achieve uniform Signal-to-Noise Ratios (SNRs) for all receivers.

According to maximum a priori criteria, the ML detector is the most effective detector for estimating the transmit symbol vector from all conceivable transmit vectors. When using a modulation strategy, the real-valued signal set ($A = [a_1, a_2, \dots, a_L]$) is used. For example, the Binary Phase Shift Keying (BPSK) signal is set to $A = [-1, 1]$, but the 16-QAM signal is set to $A = [-3, -1, 1, 3]$. This makes it challenging to implement ML in vast MIMO systems because of the exponential rise in computational complexity. As a result, linear and ML detectors have distinct performance and complexity trade-offs. A search-based technique is proposed for huge MU-MIMO systems to balance this trade-off. While linear detectors can provide superior performance because to their higher complexity, likelihood ascent search (LAS) is a neighborhood search-based detector that can deliver sub-optimal results when compared to an ideal ML detector.

The LAS is recommended for large-scale MU-MIMO systems with LR pre-coding, which is briefly discussed in Section 5, in order to attain near-optimal performance. As a result, for BPSK and 16-QAM, L is equal to 2 and 4, respectively.

5. Proposed MU-MIMO System Identification Using LLL-Based LR and LAS

For MU-MIMO systems, channel capacity grows linearly with the number of antennas at both transmitter and receiver terminals. If you want to maximize your spectral efficiency, you can put many antennas at both the user and the BS. The receiver complexity of large-scale MIMO systems is a major drawback. For large-scale MIMO systems, the likelihood ascent search (LAS) detector is recommended. With the LAS detector, linear average per-bit complexity is provided with acceptable BER performance, especially in huge structures. At each step of the algorithm's journey, the LAS algorithm attempts to find the most optimal set of bit vectors. The LAS update rule is used to design the bit vector sequence. It begins with an initial solution vector (the result of using either the ZF or MMSE detectors) and then searches for the best possible neighborhood solutions by

computing the ML detector, which then yields the best possible neighborhood solution. The new initial vector is chosen if the neighborhood solution vector is less expensive than the ML cost function. Repeating this until a minimum is reached, an output vector is then announced.

The LAS algorithm, in contrast to the ML detector, conducts a local search for every transmitted symbol. So, it's able to deliver satisfactory results with a less amount of calculations. Initial vector selection is another problem faced by the LAS algorithm. A LR pre-coded LAS detection for MU-MIMO systems has been presented that can reduce both MUI and IAI in order to address this issue. **Algorithms for LR and LLL assisted detectors for the MIMO system are as follows:**

1. **Inputs:** $y, H, \tilde{H}, x, b, T, K, A, i$
2. **Output:** \hat{b}_{LR-LAS}
3. Initialization $k=1, i=1$.
4. $H^k T^k \leftarrow \tilde{H}^k$; LLL based LR precoding
5. $T^{k-1} b^k \leftarrow x^k$; Lattice precoded signal vector.
6. $\hat{x}_{LR-MMSE}^k \leftarrow \left(\tilde{H}^{kH} \tilde{H}^k + \sigma_n^2 I_{N_r} \right)^{-1} \tilde{H}^{kH} y$; LR based MMSE detector for lattice signal vector.

Define and selection of search set

7. Define $A = [a_1, a_2, \dots, a_L]$; where value of L depend on the specific modulation used.
8. $p \leftarrow \hat{b}_{LR-MMSE}$, where $p = [p_1, p_2, \dots, p_{2N_r}]^T$; initial solution vector for LAS Detector.
9. **for** $n = 1$ to $2N_r$
10. $i \leftarrow n$, index of desired data symbol.
11. **for** $j = 1$ to L
12. $p_j = A_j$
13. $\text{cost}_j \leftarrow \|y - \tilde{H}p\|^2$
14. **end**
15. Choose A_{opt} that yields minimum 'cost' from L samples.
16. $p_j = A_{opt}$
17. **end**
18. $\hat{b}_{LR-LAS} \leftarrow p$ Choose solution of LR assisted LAS MUD.

6. Simulation Analysis

A large-scale MU-MIMO system's suggested LLL preceded LR assisted LAS detector was simulated and evaluated. As an example, the suggested detector's simulation results are compared to those of traditional Zf (MMSE), Zf (LAS), and LAS detectors in terms of the number of bits per second that they can detect. The BER of UE1 is used to make these comparisons. Large-scale MU-MIMO systems' uplink models include a BS receiver with enormous antennae and many UEs. Rayleigh flat fading is supposed to represent the wireless channel between UEs and the BS (N. Yee & J. P. Linnartz, 1993). This large-scale MU-MIMO system's simulation parameters are listed in Table 1.

Table 1
Attributes for Simulation

Attributes	Depiction
Antennas for each user (M_r)	8
Users (K)	20
Frame data	200
Receiving antennas (N_r)	256
Modulation type	16-QAM, BPSK
Size of each data frame's symbol set	2000
LR reduction factor δ	0.75
utilized channel	Flat Fading Rayleigh
LLL maximum iterations	4
BPSK, Binary Phase Shift Keying	

Different detectors are studied in terms of both BER execution and complexity analysis. The results shown here are based on 1000 (NF) information frames, each of which contains 3000 (M) information symbols. Table 1 outlines the rest of the simulation parameters. Between channel "a" and channel "b," three distinct nonlinear properties can be added from [21]:

$$\begin{aligned}
 \text{NL} = 0: & b = a; \\
 \text{NL} = 1: & b = \tanh(a); \\
 \text{NL} = 2: & b = a + 0.2a^2 - 0.1a^3; \\
 \text{NL} = 3: & b = a + 0.2a^2 - 0.1a^3 + 0.5\cos(\pi a);
 \end{aligned}$$

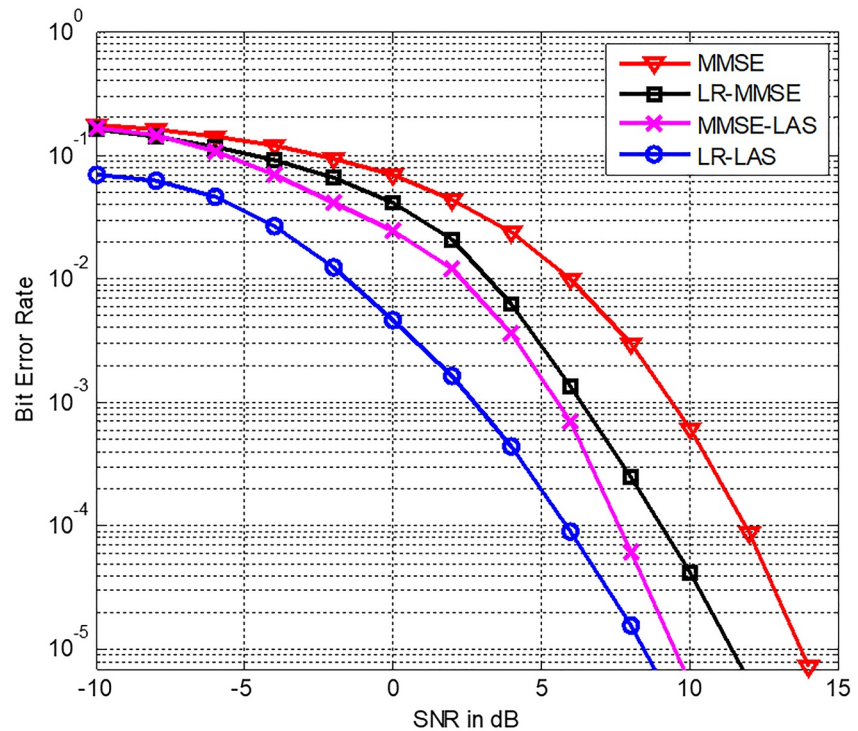


Figure 3. All users' average bit error rate performance when sending Binary Phase Shift Keying signals with minimum mean square error, LR-MMSE, MMSE-LAS, and LR-LAS detectors.

NL = 0 refers to a linear MC-CDMA model, while NL = 1 denotes a nonlinear model that may be caused by saturated power amplifiers in the system. Nonlinear models with $N = 2$ and NL 3 can be arbitrary.

Different nonlinear distortions and E_b/N_0 values affect the average BER of four different MC-CDMA system users. The average BER for Maximal Ratio Combining (MRC), MMSE, and IB-DFE receivers has been calculated and compared to that of the ideal ML one. If the MC-CDMA system suffers from substantial non-linear distortion, linear detectors such as MRC fail to attenuate these distortions and leave residual interference, as shown in this picture. Consequently, while linear receivers work well in linear and mildly non-linear systems like NL-0, NL-1, and NL-2, they suffer a considerable performance loss in severe non-linear models (NL-3). It is possible to achieve acceptable performance in such a situation by employing interference cancellation feedback.

With increasing SNR, the suggested LLR-predecessor-assisted LAS detector is tested against the classical detector, and the BER performance is evaluated (SNR). BER comparison between several detector types utilizing a BPSK modulation technique is shown in Figure 3. For the 16-QAM modulation system, the BER of several detectors is shown in Figure 4. Lower order modulation techniques provide higher overall BER performance, as can be seen from these numbers, which show greater performance with BPSK modulation than with 16-QAM modulation. n-coded ZF detector results in poor BER performance because it mitigates partial MUI without nullifying IAI, but LR pre-coded ZF detector mitigates partial MUI after IAI is nullified. LR-ZF detectors outperform un-coded ZF detectors in this regard. As a result, the MUI is more important than the IAI in simulations since there are more users than antennae in each UE. For this reason, it has a higher performance gain than ZF and LR-ZF detectors when used with the ZF assisted LAS detector. Last but not least, the suggested LR precoded LAS is constantly beating all conventional detectors as it attempts to minimize IAI and MUI at once.

LR-LAS detectors need an SNR of 6 dB, but ZF-LAS detectors need an SNR of 12 dB, while LR-ZF detectors need an SNR of 9.5 dB, and ZF-LAS detectors need an SNR of 6 dB. This is illustrated schematically in Figure 3. As shown in Figure 4, the suggested LR-LAS detector requires an SNR of 7.6 dB to achieve the same 10^{-4} error floor, whereas the SNR requirements for ZF, LR-ZF, and ZF-LAS detectors are each 13.8, 11.9, and 9.7 dB. For the ZF, LR-precoded and LR-assisted ZF, as well as the ZF assisted LAS and LR-assisted LAS detection schemes,

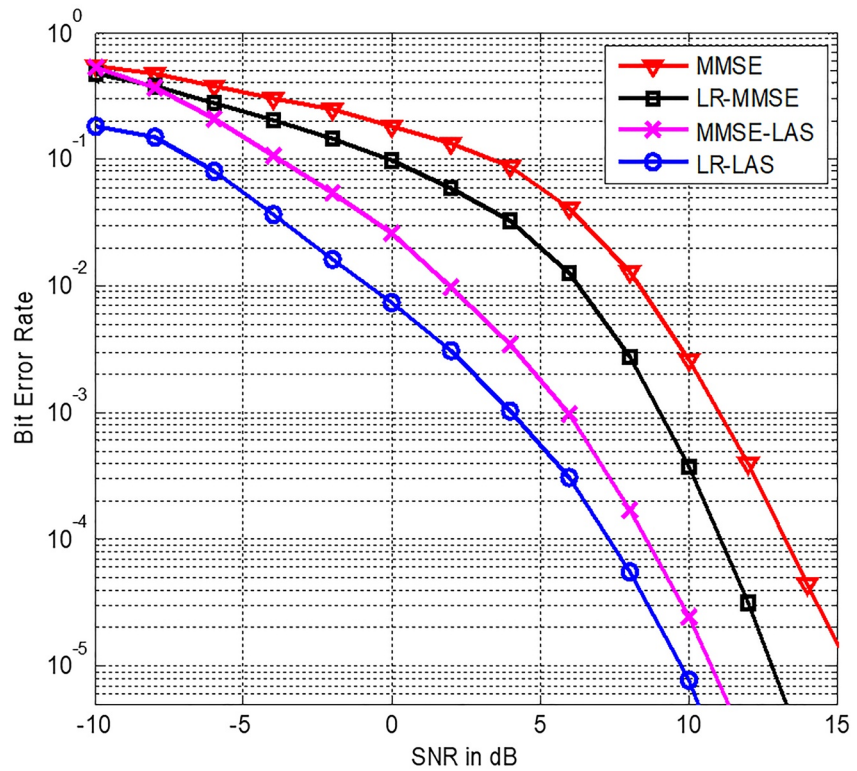


Figure 4. All users' average bit error rate performance when sending 16-QAM signals with minimum mean square error, LR-MMSE, MMSE-LAS, and LR-LAS detectors.

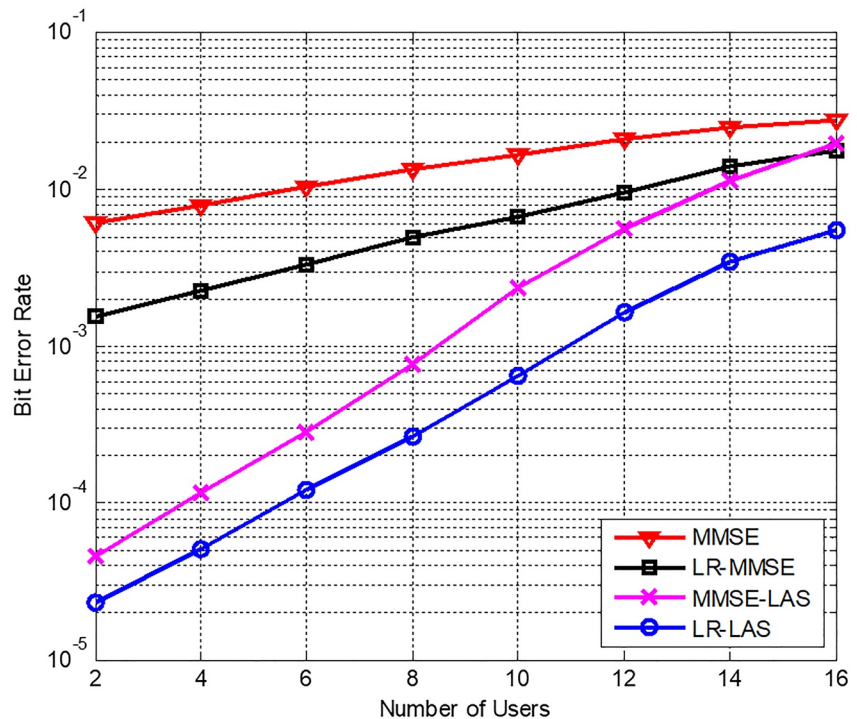


Figure 5. Average bit error rate performance of minimum mean square error, LR-MMSE, MMSE-LAS and LR-LAS detectors for increased number of users transmitting Binary Phase Shift Keying signals.

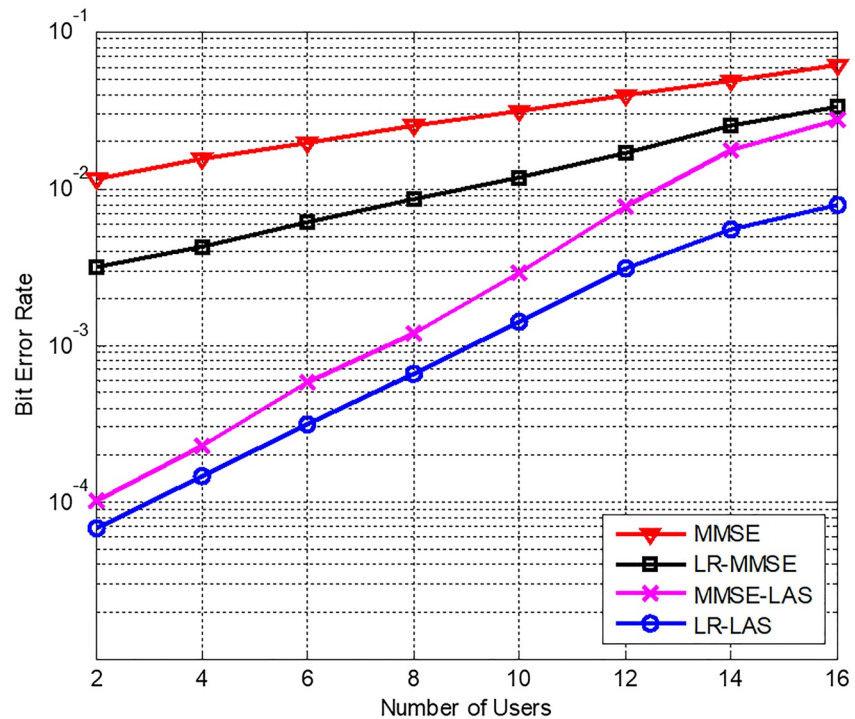


Figure 6. Average bit error rate performance of minimum mean square error, LR-MMSE, MMSE-LAS and LR-LAS detectors for increased number of users transmitting 16-QAM signals.

the performance of the BER is further examined while adjusting the number of UEs, as shown in Figures 5 and 6. As the number of UEs grows, the MUI gets bigger.

As a result, as the number of UEs grows, so does the BER.

The LAS detector regularly outperforms the ZF and LR precoded ZF detectors in terms of preventing more serious MUI. In addition, as shown in Figures 5 and 6, the proposed LR assisted LAS is able to minimize both IAI and substantial MUI, resulting in similar outcomes for BPSK and 16-QAM. BER of 0.0007185 is achieved using the suggested LR-assisted LAS detector with BPSK signals from up to 10 UEs, while ZF, LR precoded ZF, and LAS detectors based on ZF each have BERs of 0.01845, 0.007477, and 0.00261268 (see Figure 5). Furthermore, while accommodating 10 users with 16QAM signals, the suggested ZF, precoded ZF, and ZF assisted LAS detectors have BER values of 0.35291233, 0.1313625 and 0.02375413, respectively (Figure 6).

There are ML cost function evaluations in this complexity analysis, and the number of evaluations is shown in Table 2. Because the best ML detector uses a global search method, it has exponentially high computational cost, making it unsuitable for use in large-scale MIMO systems.

But because it searches for a solution locally at each transmitting antenna, the LAS is incredibly simple. On a per-bit basis, the average complexity of the search set in simulation analysis is $O(N_T)$. LAS is a simple detector in the low complexity detector family. It has a linear average bit complexity due to its usage of local search.

However, the LAS detector's initial vector computation is the source of the detector's computational complexity. The initial solution vector for the LAS detector is typically the ZF/MMSE detector's solution vector. Consequently, the LAS algorithm's overall per-symbol complexity is $O(N_T N_R)$, which makes it ideal for dealing with high numbers of dimensions. In addition, $O(N_T N_R)$ computations can be performed using the LR assisted LAS detector. When using LR assisted LAS, the amount of computation required is significantly less than when using ML detectors. Although the proposed detector is capable of near-optimal performance, it does not yet exist.

Table 2
Cost Function Evaluation Complexity of Various Detectors

Detector	Complicated nature of BPSK	Complexity scale
ML Detector	$2^{240} \approx 10^{72}$	L^{2N_T}
Proposed LR-LAS	0.48×10^3	$2N_T X L$
BPSK, Binary Phase Shift Keying		

7. Conclusions

In this paper, an LLL-based LR aided LAS detector for large-scale MU-MIMO systems is suggested. It's not all good news for the MU-MIMO system, however, as it suffers from IAI at each user unit and MUI at the receiver unit BS. Making a MUI and IAI suppressing low-complexity receiver is a difficult task. According to the author's knowledge, the majority of previous studies focused on one or more of these interferences. The suggested work, on the other hand, successfully reduces the performance-complexity gap while also mitigating IAI and MUI. LLL-based pre-coding schemes for each UE handle IAI and MUI, while the LR-LAS detector mitigates MUI for each BS. The suggested LLL-based LR-LAS approaches, as compared to the traditional detectors, achieve ML performance and have a significant complexity gain over the ML detector. According to the results of the simulation, the suggested LR assisted LAS methodology has a gain of 4.95–11.9 dB over the standard methods. As a result, the technique under consideration provides better performance while requiring less computational complexity to implement.

Data Availability Statement

There are no specific data for this manuscript. All the results presented within this research work have been achieved by Matlab R2016a.

Acknowledgments

Dr. Mohammad Alibakhshikenari acknowledges support from the CONEX-Plus programme funded by Universidad Carlos III de Madrid and the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie Grant agreement No. 801538. Also, this work was supported by Ministerio de Ciencia, Innovación y Universidades, Gobierno de España (Agencia Estatal de Investigación, Fondo Europeo de Desarrollo Regional -FEDER-, European Union) under the research Grant PID2021-127409OB-C31 CONDOR. Funding for APC: Universidad Carlos III de Madrid (Read & Publish Agreement CRUE-CSIC 2022).

References

- Bagadi, K. P., & Das, S. (2013). Neural network-based multiuser detection for SDMA-OFDM system over IEEE 802.11 n indoor wireless local area network channel models. *International Journal of Electronics*, 100(10), 1332–1347. <https://doi.org/10.1080/00207217.2012.743085>
- Bagadi, K. P., & Das, S. (2014). Multiuser detection in SDMA-OFDM wireless communication system using complex multilayer perceptron neural network. *Wireless Personal Communications*, 77(1), 21–39. <https://doi.org/10.1007/s11277-013-1492-2>
- Bagadi, K. P., Annepu, V., & Das, S. (2016). Recent trends in multiuser detection techniques for SDMA-OFDM communication system. *Physical Communication*, 20, 93–108. <https://doi.org/10.1016/j.phycom.2016.07.001>
- Bagadi, K., & Das, S. (2013). Efficient complex radial basis function model for multiuser detection in a space division multiple access/multiple input multiple output orthogonal frequency division multiplexing system. *IET Communications*, 7(13), 1394–1404. <https://doi.org/10.1049/iet-com.2012.0688>
- Bagadi, K., & Das, S. (2014). Minimum symbol error rate multiuser detection using an effective invasive weed optimization for MIMO/SDMA-OFDM system. *International Journal of Communication Systems*, 27(12), 3837–3854. <https://doi.org/10.1002/dac.2579>
- Bagadi, K., Ravi Kumar, C. V., Sathish, K., Alibakhshikenari, M., Virdee, B. S., Kouhalvandi, L., et al. (2022). Detection of Signals in MC-CDMA using a novel iterative block decision feedback equalizer. *IEEE Access*, 10, 105674–105684. <https://doi.org/10.1109/ACCESS.2022.3211392>
- Buzzi, S., & D'Andrea, C. (2018). Energy efficiency and asymptotic performance evaluation of beamforming structures in doubly massive MIMO mmWave systems. *IEEE Transactions on Green Communications and Networking*, 2(2), 385–396. <https://doi.org/10.1109/TGCN.2018.2800537>
- Challa, N. R., & Bagadi, K. (2020). Likelihood ascent search detection for coded massive MU-MIMO systems to mitigate IAI and MUI. *Radiation and Communications Systems*, 63(5), 223–234. <https://doi.org/10.3103/s0735272720050015>
- Challa, N. R., & Bagadi, K. (2021). Design of large scale MU-MIMO system with joint precoding and detection schemes for beyond 5G wireless networks. *Wireless Personal Communications*, 121(3), 1627–1646. <https://doi.org/10.1007/s11277-021-08688-6>
- Ereceg, V., Hari, K. V. S., Smith, M. S., Baum, D. S., Sheikh, K., Tappenden, C., et al. (2001). Channel models for fixed wireless applications 802. *Contribution IEEE*.
- Guo, J.-C., Yu, Q.-Y., Sun, W.-B., & Meng, W.-X. (2021). Robust efficient hybrid pre-coding scheme for mmWave cell-free and user-centric massive MIMO communication. *IEEE Transactions on Wireless Communications*, 20(12), 8006–8022. <https://doi.org/10.1109/TWC.2021.3089501>
- Hong, J., Rodríguez-Piñero, J., & Yin, X. (2020). FDD channel inference methods with experimental performance evaluation. *IEEE Access*, 8, 10491–10502. <https://doi.org/10.1109/ACCESS.2020.2965290>
- Imaudin, M. D., Ravi Kumar, C. V., & Kalapraveen, B. (2020). *Signal detection in MC-CDMA system using ELM receiver to mitigate MAI and non-linear distortion*. Asian Research Publishing Network (ARP).
- Jayaprabath, Ravi Kumar, C. V., & Rahul Varma, C. (2019). *Performance analysis of interior and exterior routing protocols*. Asian Research Publishing Network (ARP).
- Jitish, Ravi Kumar, C. V., & Kalapraveen, B. (2020). *LPWAN technologies for IoT deployment.11* (pp. 285–296). International Journal of Electrical Engineering and Technology.
- Kalapraveen, B., & Ravikumar, C. V. (2016). Performance analysis of ipv4 to ipv6 transition methods. *Indian Journal of Science & Technology*, 9(20). <https://doi.org/10.17485/ijst/2016/v9i20/90005>
- Kibona, L., Liu, J., Liu, Y., & Wang, D. (2021). Impact of Circuit Intake Power on the Spectral Energy Efficiency of Massive MIMO With Channel Estimation Errors. *IEEE Access*, 9, 133820–133834. <https://doi.org/10.1109/ACCESS.2021.3113782>
- McCormick, A. C., & Al-Susa, E. A. (2002). Multicarrier CDMA for future generation mobile communication. *Electronics & Communication Engineering Journal*, 14(2), 52–60. <https://doi.org/10.1049/ecej:20020202>
- Miller, L., & Lee, J. (1998). *CDMA systems engineering handbook* (Vol. 1). Artech House Press.
- Patra, J. C., Pal, R. N., Baliarsingh, R., & Panda, G. (1999). Nonlinear channel equalization for QAM signal constellation using artificial neural networks. *IEEE Transactions on Systems, Man, and Cybernetics*, 29(2), 262–271. <https://doi.org/10.1109/3477.752798>
- Prasad, R. (2004). *OFDM for wireless communications systems* (Vol. 2). Artech House Press.
- Prasad, R., & Hara, S. (1997). Overview of multicarrier CDMA. *IEEE Communications Magazine*, 35(12), 126–133. <https://doi.org/10.1109/35.642841>

- Proakis, J. G. (1995). *Digital communications* (Vol. 4). Mc-Graw Hill Press.
- Ravikumar, C. V., & Bagadi, K. P. (2016b). Robust neural network based multiuser detector in MC-CDMA MAI mitigation. *Indian Journal of Science and Technology*, 9(30), 95994. <https://doi.org/10.17485/ijst/2016/v9i30/95994>
- Ravi Kumar, C. V., & Bagadi, K. P. (2017a). Design of MC-CDMA receiver using radial basis function network to mitigate multiple access interference and nonlinear distortion. *Neural Computing and Applications*.
- Ravi Kumar, C. V., & Bagadi, K. P. (2017b). MCCDMA receiver design using recurrent neural networks for eliminating multiple access interference and nonlinear distortion. *International Journal of Communication Systems*.
- Ravikumar, C. V., & Bagadi, K. P. (2017c). Receiver design using artificial neural network for signal detection in MC-CDMA system. *International Journal of Intelligent Engineering & Systems*.
- Ravi Kumar, C. V., & Kalapraveen, B. (2019). Design of multilayer perceptron receiver for MC-CDMA system to mitigate multiple access interference and non-linear distortion. *Neural Computing & Applications*, 31(2), 1263–1273.
- Ravikumar, C. V., & Saranya, K. C. (2016a). Implementing mobile adhoc networks with improved. AODV protocol" *International Journal of Applied Engineering and Research*, 11(9), 6284–6289.
- Ravikumar, C. V., & Saranya, K. C. (2016b). Improving Interference alignment of Gaussian MIMO x channel and Gaussian MIMO z channel. *International Journal of Applied Engineering Research*, 11(9).
- Ravikumar, C. V., & Venugopal, P. (2018). Adaptive cruise control and cooperative cruise control in real life traffic situation. *International Journal of Mechanical Engineering & Technology*, 9(13), 578–585.
- Ravikumar, C. V., Bagadi, K. P., Sairam, P., Sundeeep, M., Praveen Bagadi, K., & Annepu, V. (2016a). Performance analysis of HSRP in provisioning layer-3 gateway redundancy for corporate networks. *Indian Journal of Science and Technology*, 9, 89851. <https://doi.org/10.17485/ijst/2016/v9i20/89851>
- Steele, R., & Hanzo, L. (1999). *Mobile radio communications* (Vol. 2). John Wiley and IEEE Press.
- Verdu, S. (1998). *Multiuser detection* (Vol. 1). Cambridge University Press.
- Viterbi, A. J. (1995). *CDMA: Principles of spread spectrum communication* (Vol. 3). Addison-Wesley Press.
- Weinstein, S. B., & Ebert, P. M. (1971). Data transmission by frequency-division multiplexing using the discrete Fourier transform. *IEEE Transactions on Communications*, 19(5), 628–634. <https://doi.org/10.1109/tcom.1971.1090705>
- Yan, Y., & Ma, M. (2015). Novel frequency-domain oversampling receiver for CP MC-CDMA systems. *IEEE Communications Letters*, 19(4), 661–664. <https://doi.org/10.1109/lcomm.2015.2391103>
- Yee, N., & Linnartz, J. P. (1993). Multicarrier CDMA in indoor wireless radio networks. In *Proceedings of annual international symposium on personal, indoor, and mobile radio communications*.