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Adaptive Power Allocation Design of Beyond 6G Highly Dense NOMA-Massive MIMO Infinity-Norm Box Detection Technique

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ABSTRACT

A significant increase in 5G cellular transmission capacity might be achieved by employing Multi-Input Multi-Output (MIMO) antenna systems. It is highly expected that the increasing coverage and capacity for beyond 6G may demand the energy efficient transmission and design of Massive MIMO detectors (MD) systems. The likelihood of larger detection errors may significantly increase as payload demand rises. Due to the variable spatial resolutions enhancing the detection probability efficiency for multiple I/O antenna (MIMO) systems is a difficult task. Papers prime objective is to design the novel NOMA-Massive MIMO system based on the fuzzy adaptive power allocation law and to simulate effectiveness of different detectors. It is proposed to design an efficient Infinity-Norm detector (IND) by employing the alternating directions methodology using the multipliers (ADMM) convex optimization for massive MIMO system. As a novelty the tweaking of MMSE estimate is proposed at the IND-ADMM initialization. This tweaked estimate has the potential to improve beam-forming performance and background noise separation, hence increasing detection accuracy. Major advantage of method is its fast speed or convergence rate. This paper contributes to validating and expand NOMA-Massive MIMO system using adaptive NOMA power allocation and IND-ADMM detector design for higher capacity detection. It is proposed to investigate the error rates for different MIMO sizes and different constellation orders of M-QAM. The new formulation of adaptive reduced constellation order (RCO) is proposed as the density of users and massive MIMO channel size is increased. The performance of Box based detectors is compared for seven MIMO detectors as matched filter (MF), MMSE, Neumann-series approximation, Gauss-Seidel (GS), conjugate-gradient (CG), and proposed RCO-ADMIN detectors. The Monte Carlo (MC) simulation of MIMO performance is evaluated using detection error probability and execution times for these detection techniques. ADMM based IND detectors are faster and offer significant improvement in capacity with proposed iterative approach and BER more than 100 times at 5dB less SNR.

1. INTRODUCTION

Future 5G wireless communications will use a multiple-I/O (MIMO) antenna system with a significant number of trans-receiver antennas. Beyond 5G and 6G, cellular technologies have various prospects for expanding MIMO antenna systems in the future [1]. The majority of early study focuses on expanding the reach and elevating the energy effectiveness of MIMO transmission setups. For next-generation 6G systems of communication, to satisfy consumer demands at speed with better quality of services (QoS) Massive-MIMO (M-MIMO) technique are essentially required. A large upstream receiver's various transmitters and radio frequency (RF) chains rapidly increased the degree of complexity of M-MIMO detectors [2]. Discovering best M-MIMO detection method with the lowest level of difficulty with the greatest efficiency has therefore gained a lot of attention last decades.

Therefore, the scope of the paper is to investigate and design the efficient M-MIMO detector. In recent times Non-Orthogonal Multiple Access (NOMA) has emerged significant potential to enhance the capacity of existing cellular systems. The power allocation and number of users to be adopted is a big challenge as the system goes to massive M-MIMO. This paper has proposed a mathematical power adoption law corresponding to the random user's distances and the M-MIMO sizes for the NOMA implementation.

1.1 Problem statements

Unlike conventional orthogonal system, in NOMA several users can share identical resources by using varying power levels sharing. It requires sophisticated power allocation techniques to maximize system performance employing this approach. The main restriction on the NOMA system's design is transmitter's fixed and limited power. Abbreviations and Nomenclatures used are given in the Table 1.

Table 1. Abbreviations along with nomenclatures used in the study

Abbreviations		Abbreviations		Notations	
AWGN	Additive White Gaussian Noise	M-MIMO	M-MIMO	$M = L$	Constellation Order
BPSK	Binary-Phase Shift-Keying	IND	IND	d	NOMA user distance vector
BER	Bit Error Rate	NOMA	NOMA	a	NOMA Power scaling factor
BOX-DCD	box-constrained dichotomy coordinates descending	FDMA	Frequency Division Multiple Access	y	MIMO receive vector
MIMO	Multi-Input Multi-Output	QPSK	Phase Shift Key	Iteration	Monte Carlo Simulation Titration count
BS	Base Station	QAM	Quadrature Amplitude Modulation	Itr	ADMIN loop titrations
EE	Energy Efficiency	QoS	Quality of Service	$BER_{SNR_{dB}}$	Bit Error Rate for SNR
ZF	Zero Forcing	RCO	Reduced Constellation Order	p	Lop count for order of QAM
MF	Matched Filter	MMSE	Minimum Mean-Square Error	u	An integer for SR loop
SCCC	Serially Concatenated Convolutional Code	SIC	Successive-Interferences -Cancelation	bit_k	k^{th} $transmitt$ Data symbol
ADMM	Alternating directions methodology multipliers	OIMF-SIC	Ordered Improved Multiple Feedback SIC	$H_{1,2}$	Channel realization Matrix for NOMA
5G	5th Generation cellular	6G	6th Generation cellular	S	Number of QAM symbols
QR	Quadratic Regularization	CG	Conjugate Gradient	SR	Sum rate for NOMA-MIMO
MU	Mobile Unit	CF	Cell Free	Mt	Number of UE antennas
MLD	Maximum Likelihood Detector	CSI	Channel State Information	N0	Noise per receivers
GS	Gauss-Seidel	NSA	Neumann-series approximation	Nr	Number of BS antennas
LTE	Long Term Evaluation	SNR	Signal to Noise Ratio	D	Diagonal matrix
DL	Down Link	AID	Approximate Inversion Detectors	A	Approximate invasion matrix
MIA	Matrix Inversion Approximation	SER	Symbol Error Rate	X^h	Detected vector for evaluation
SD	Sphere-Decoding	UOWC	Underwater-optical wireless comm.	T	Power allocation t
DOA	Direction-Of-Arrival	LASSO	Low absolute shrink select operator	C	Chanel Capacity

The concept of adaptive power allocation consists of dynamically modify power levels in response to current channel data. Therefore, paper proposed to design novel NOMA-Massive MIMO system based on fuzzy adaptive power allocation law and to simulate effectiveness of different detectors. The highly massive beyond 6G huge 64 to 256 antennas transmitting structure is considered with large number dense receiver diversity 16 to 256 users, antenna for M-MIMO system detection. Since NOMA users are randomly placed in the network thus it's a big challenge to efficiently allocate power to users. The theoretical background is to underlying proposed adaptive power allocation based on principles of ratio of user's distance from base station. It is assumed to allocate less for closer users and more for distant ones. This paper proposed a mathematical formation for achieving the solution.

Selection of the suitable accurate, mathematical model for MD is required for designing the effectiveness of massive MIMO systems, M-MIMO is indeed an extension of the traditional MIMO frameworks by combining the antennas together around the base station (BS) transmitter and mobile unit (MU) receivers for improve the capabilities of the communication systems. The abbreviations used in manuscript are shown in Table 1. M-MIMO has become the next generation technology used in 5G LTE, a radio interface for the physical layer for cellular systems that allows transmission bandwidths of 20MHz or more. Designing the best choice of MD for such a system's is still an open field of near research. Adopting IND is highly advantageous since they provide superior bit error rate (BER) performance over linear detectors, particularly for high-interference settings. These IND detectors may offer less computation cost and be more robust than linear detectors. Another advantage of IND is that they may be scaled to a massive number of antennas more readily.

Theoretically, the design of IND represents the data to be analyzed as a vector, infinity norm is determined as the maximum absolute value of the data vector. Another name for the IND-ADMM is ADMIM, which is an iterative detection technique. The advantage of ADMM-based techniques over conventional MIMO detection algorithms is that they can handle MD objective functions for M-MIMO structures more efficiently. This has been noted that conventional detectors by Chang and Chang [3], were computationally complex. But the IND detector can be implemented on multi-processing hardware due to its fast convergence.

1.2 Assumptions

To make mathematical models used for MIMO detector designs simpler, the following assumptions are made.

- The channel state information and data signal are randomly generated. It is assumed that trans-receiver has perfect info of channel.
- Channel is assumed to be flat.
- The additive white Gaussian Noise (AWGN) channel noise model is assumed.
- Total BS transmitting power is assumed to be fixed.
- Massive MIMO assumes using of numerous transes receive antennas which is futuristic.

1.3 Contribution of work

The purpose of this work is to design and test an efficient IND using ADMM multipliers based convex optimization for massive MIMO system capacity enhancement. This research contributes to validate and expand MIMO system to the concept of NOMA-Massive MIMO for higher capacity detection. The capacity improvement based on NOMA-MIMO system is evaluated. The performance is examined based on the error rates calculated at the receiver end after the detection of true information. The research contributed to adopt the reduced constellation order (RCO) with respect to extending capacity and MIMO dimensions. The performance of Box based detectors is compared for seven MIMO detectors as matched filter, MMSE, Neumann-series approximation, Gauss-Seidel (GS), conjugate-gradient (CG), and RCO-ADMM detectors. The execution time performance is also assessed for the various detection methods, final and major contribution of paper is to design the adaptive NOMA power allocation law for ever increasing MIMO sizes. The power allocation parameters are adopted for the random location of users in the system.

2. NOMA-MASSIVE MIMO CHALLENGES

NOMA-Massive MIMO is one of the exciting technologies that have the ability to greatly increase cellular network spectral efficiency and capacity. Massive MIMO use many antennas to provide beam-forming with spatial multiplexing, whereas NOMA employs changing levels of power to allow different users to share the same spectrum resource. Combining the benefits of NOMA and Massive MIMO may significantly improve the spectral efficiency and capacity. Besides these advantages there are various issues that must be overcome before NOMA massive MIMO can be extensively used. Among these major challenges are shown in the cluster diagram in Figure 1.

As clear from Figure 1 that major challenges are error performance improvement, efficient channel estimation, power allocation, and the efficient and fast MIMO detection designs. The adaptive power allocation may require additional hardware in the network thus leads to more power consumption. This paper manly focus on the NOMA power-allocation, and effective massive MIMO detection based on error performance evaluation. It is highly required to enhance the error rate performance of MD. Handling channel interference is also a big issue.

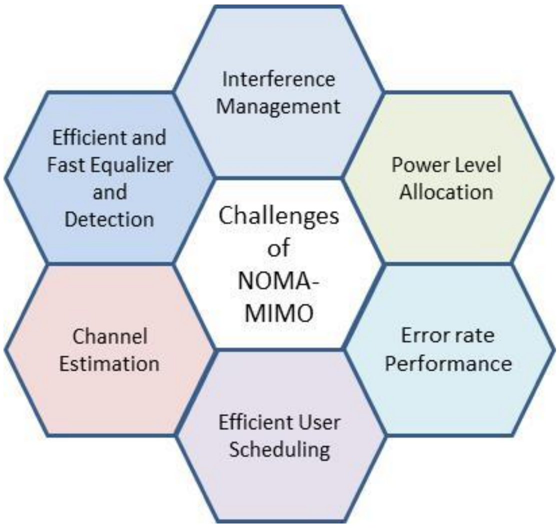


Figure 1. Various challenges of NOMA-MIMO communication system

3. REVIEW AND CHALLENGES

Lot of recent research has been centered across designing an efficient detection method for the M-MIMO communication systems. This section has presented the review of detection methodologies, respective challenges, and limitations.

3.1 Classification of MIMO detection techniques

A survey of M-MIMO based detection techniques has been presented by Quan et al. [1]. They classified various detection techniques. The most frequently used MIMO detection techniques are classified in Figure 2 opted for decreasing the receiver side error rates to improve detected signal quality. This paper is aimed to consider linear detectors to avoid excessive computation time.

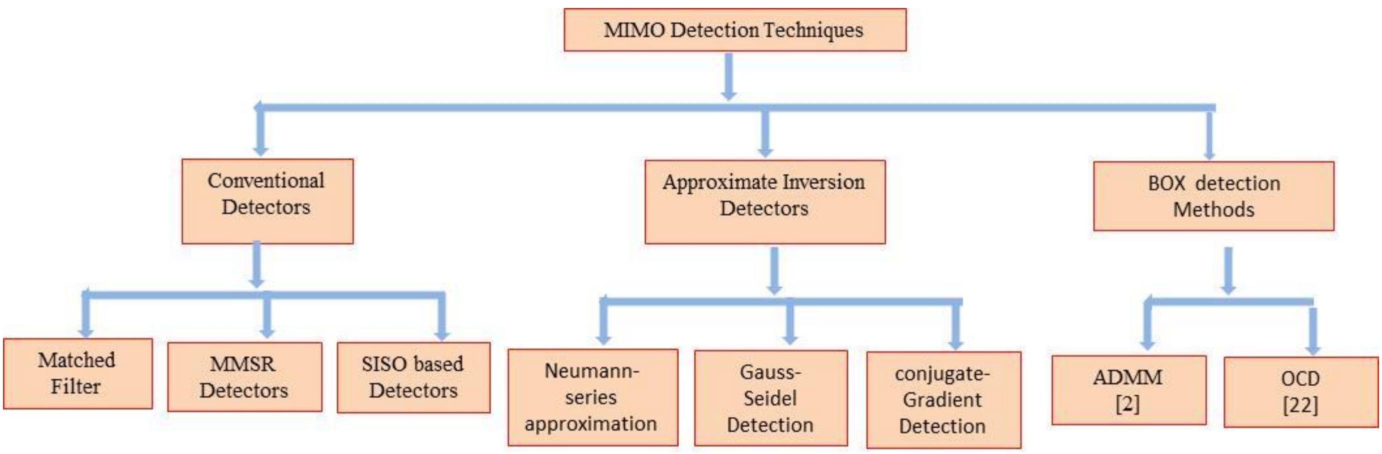


Figure 2. Classification of the several MD methods used in this study

Quan et al. [1] has studied and introduced a rectangular M-QAM symbol detection that uses BOXDCD, a combination de-regularized and box-constrained based dichotomous coordinates descending method. De-regularization approach has increased the energy of the solution. Box constraint forces de-regularization to take place within the defined rectangular border. The mathematical results show that their box detectors outperform on state-of-the-art detection approaches significantly. According to Borges et al. [2], telecoms have evolved into a crucial component of society as a whole therefore the need for trustworthy and high-performance systems has emerged as the primary goal for researchers and engineers. As indicated by cutting-edge research, massive MIMO is the fundamental technology for 5G, 6G and beyond. Amongst the major benefits, in addition to better energy efficiency (EE), including broad spatial multiplexing along with increased diversity. Chang and Chang [3] have designed the Maximum Likelihood (ML) based MIMO detection it works significantly good at lower signal to noise ratio (SNR) values.

Sufyan et al. [4] presented the good extended survey of the various challenges and technologies used for the 5G and beyond wireless networks. Zhang and Haenggi [5] stated that performance of successive interference cancellation (SIC) in wireless networks with arbitrary fading distribution and power-law path loss is studied using a unified framework in this paper. The efficiency of SIC is analytically described as a function of numerous system variables.

The findings imply that particularly in networks with high dimensions and low path loss exponents, the marginal value of allowing the receiver to successively decode k users decreases extremely quickly with k. However, SIC is especially helpful when users are grouped together near the receiver and/or extremely low-rate codes are applied.

Liu [6] presented a thorough overview of the various designs and VLSI hardware architecture for MIMO system design in their paper. To reduce computational complexity, these designs employ cutting-edge truncated GS method, and ADMIN techniques. To enhance hardware architecture, they employ iterative processing units and pipeline designs. These techniques have enhanced MIMO performance in various ways and to various degrees. Bjørn and Proakis [7] had taken MIMO wireless communication systems into account, by using a number of transmit and receive antennas to boost data rates and achieve diversity in fading multipath channels. They first concentrate on an encoded system and determine the best and worst receiver architectures for it in both inter symbol interference-free and Rayleigh fading. Bjørn then took into account coded MIMO systems. The code and the multipath channel serve as the constituent codes in what is known as a serially concatenated convolutional code (SCCC) for the coded system. The MIMO antennas enable increased spectral efficiency for a given total transmit power, according to Abdaldaim [8], by adding extra channels, the system's capacity can be enhanced. In this article, MIMO signal detection was examined and discussed in context of minimum mean square error (MMSE) equalizer and the zero forcing (ZF) equalizer used in the receiver design to lower the average bit error rate (BER) in Rayleigh flat-fading channels. But with increasing number of antennas, it is still a challenge to improve BER.

Mandloi et al. [9] have proposed to design the near-optimal MIMO detection, by using an improved multiple feedback-SIC (IMF-SIC) approach and an ordered IMF-SIC (OIMF-SIC) algorithm. The SIC detector's multiple feedback (MF) strategy, in particular, is based on idea of the shadow region. If a decision is made in the shadow region, multiple nearby constellation points are used in the decision feedback loop that comes after the SIC technique, and the best candidate symbol is chosen using the maximum likelihood cost. The only limitation of method is number of iterations makes it slow for real-time uses. Obakhena et a. [10] have outlines the main uses for Cell-free (CF) mMIMO widely used for 5G and the anticipated 6G wireless networks. An introduction to M-MIMO solutions, including cellular massive MIMO, network MIMO, and CF-mMIMO, is given first, with an emphasis on the application domains and accompanying difficulties. CF-mMIMO architectures, design aspects, and system modeling are all thoroughly discussed. Nguyen et al. [11] in their research provided low-complexity multiuser detection techniques for huge MIMO systems based on Variational Bayes (VB) inference. They first look at the massive MIMO detection issues with perfect channel state information (CSI) at the receiver and demonstrate that a traditional VB technique with known noise variation produces subpar detection performance.

Manju and Ganesh [12] have presented an extended review of various MIMO detectors and their performance measures. Praveena1 et al. [13] have simulated results of SIC based MIMO-SC-FDMA detector. Shows that specified algorithm outperforms traditional detection methods and achieves greater performance with less complexity when the MIMO detector work is compared to the other approaches. Divya et al. [14] stated that massive MIMO demands higher quality of service (QoS) systems for the next-generation connectivity. In a MIMO uplink receiver with numerous antennas for wireless optical communication, the complexity of symbol detectors increased considerably due to (RF) chains because there are so many antennas and radio frequencies. As a consequence, researchers have created the MMSE-based most effective massive MIMO detection approach unique to the scenario. Albreem et al. [15] presented the survey of the various MIMO detectors using the local search, belief propagation, and the faster box based detectors and stated that these are near-optimal detectors. Suh and Barry [16] identified scalar list detection as a crucial component of the K-best detector and suggested a low-complexity, effective implementation of the scalar list detector for M-ary QAM. Our proposed slicing K-best detector is obtained by integrating the slicing list detector into the K-best framework. Dala Pegorara Souto et al. [17] presented a review of the various extremely large MIMO systems detection methods including the Intelligent Reflecting Surfaces (IRS), and CF-mMIMO which works better in 5G environments.

Rekkas et al. [18] provided an overview of machine learning (ML) techniques as well as a current analysis of ML methods used in 6G wireless communication systems. Supervised, unsupervised, and reinforcement strategies are among these procedures. Additionally, they go through unresolved problems with ML for wireless communications in general and for 6G networks in particular, as well as some possible future trends to spur more study in this subject. Lee. [19] had used dropping strategy, which eliminates the IoT devices that consume a lot of power, to try to improve the performance of Massive MIMO with Massive IoT connectivity. The spectrum and EE of Massive MIMO systems have been improved by a number of scheduling and power control approaches. Tiba et al. [20] proposed to adopt deep neural networks (DNNs) used for designing the M-MIMO ADMM based detection approach as proposed in their works to overcome the existing limitation. Utilizing an unfolding technique, it gets the capacity to compute the penalty factors. There is also a suggestion for a detector with reduced computing expense. The offered methods are capable of handling the higher-order modulated signals. Mathematical findings are provided to demonstrate the performance of the approaches suggested with respect to the previously published studies.

3.2 Review of advanced detectors

Kumar et al. [21] proposed to evaluate the unique hybrid method for 16×16, 64×64, and 256×256 MIMO architectures. There hybrid methods include Quadratic regularization QR-maximization likely detection (QR-MLD), QR-MMSE, QR-ZF equalization (ZFE), and QR-beam formation (QR-BF). With negligible complexities, the combination of methods achieved an effective bit rate of error (BER) of 10^{-3} with a 2.9dB SNR. But execution time and complexity is more. Arun Kumar and Gupta [22] presented a book on the beyond 5G technologies. They have discussed and described an in-depth examination of the main methods, difficulties, frequency distribution, initiatives, and current 5G prospects. The current report provides a thorough investigation into the problems and advancements associated to the rollout of 5G.

Various conjugated gradients (CG) approaches were proposed as in studies [23-25]. Labed and Aounallah [23] work proposed a CG based on sequential over-relaxation (SOR) approaches to build a new sequential approach that circumvents the calculation problem associated with matrix invert. They proposed a method for uplink mMIMO identification is based on the two iteration techniques' joint waterfall architecture. An approach with consistent efficiency and minimal computing complexity was produced by first applying and fine-tuning the CG technique for the first the solution, then using the SOR approach in the last iterations for terminals tasks. Wei et al. [24] has studied and examined large multiple-input multiple-output (MIMO) identification using based on models' methods of deep learning. Large MIMO networks offer greater coverage, range, and spectral performance than traditional MIMO devices. Regretfully, the gains in efficiency of computation are substantial in exchange for these advantages. Ouameur and Massicotte [25] created a massive MIMO detector design approach employing a deep expanded CG based structure. They're suggested CG method blends the benefits of offering deep instruction with an approach based on models for enabling the easy integration of domain expertise into efficient variable estimation. But the low time of execution is still a challenge for CG based methods.

Various Gauss-Siedel (GS) based MD was proposed in the studies [26-28]. Torres et al. [26] proposed to examine the integration of the SMF method to limited bandwidth and chirping sounds embedded in white noise, having been initially introduced by Torres et al. [26] as in both identification and estimate situations. Data depicted that the SMF is a workable method for signal recognition and estimate in moderate to elevated ratios of signal to noise (SNR) values, and it might be used in apathetic, actual time signal identification and estimate situations. Yao et al. [27] had proposed to model the neural detector system, called Blocking the Gauss-Networks (BGS-Net), which is based upon the Gauss iterative technique. This reduces the high cost of concurrent execution of the classic GS iteration method. By splitting up a huge inversion of a matrix into smaller matrix inversions of the and thus may decrease complication. Chataut et al. [28] designed the Symmetry Sequential Overlap Relax based Gauss-Seidel (SSORGS) approach as a novel alternative of the GS method proposed in this work. The suggested approach will deal with the difficulties in signal detection brought on by enormous MIMO technology. Additionally, we introduce a new Symmetric Sequential Over relax preconditioned (SSOR) technique and a starting strategy depending on the immediate channel conditions of the client and the starting location, which further improves the originally proposed method's rate of resolution.

Gustafsson et al. [29] explained that the level of difficulty in massive scenario is not less as typically claimed, since the difficulty of accurate techniques is nearly identical when three variables are utilized for the Entire sequence. Higher analogy, the second popular defense of the Newman series estimation, is true. The authors Shao and Zu [30] proposed an innovative joint Newtonian repetition and Friedrich serial technique to accelerate resolution. The Wiener series is reconstructed using the first repetition result of the Newtonian repetition method. They then construct an extremely likely resolution condition that can provide helpful suggestions for real-world large MIMO networks.

3.3 Review of box based detectors

The box based MIMO detectors are most frequent in recent times and are used because of their faster convergence time. Many Box detectors were proposed in literature and reviewed sequentially in this section. Quan et al. [1] studied a detection method for square m-ary (M-QAM) symbols based on combined de-regularized and box-constrained dichotomy coordinates descending (BOX-DCD) with repetitions were presented. The solution's efficiency was maximized using de-regularization. The de-regularization of the box-constraint is capable of comparing the outcome to linear the square border detectors only.

Shahabuddin et al. [31] provided a new method for detecting data and appropriate VLSI architecture for an enormous multiple users (MU) radio transmitter that combines multiple input and multiple output (MIMO). Our technique, called ADMIN, implements infinite norm restricted equalization using an alternate directional approach to multiplier (ADMM). In situations where the total amount of users is lower than the number of antennae in the BS, the iteration ADMIN method works better than linear sensors detectors. Gebeyehu et al. [32] enhanced the bit error rate (BER) and other performance indicators like gain, efficiency of energy, and spectral effectiveness. For identifying the message that was sent signal, intricate analysis is needed due to an enormous amount of users and antennas. Transmission communication signal identification is a problem in huge MIMO systems. Numerous techniques for detection, such as Matching Filter (MF), CG) GS, ZF, MMSE, and optimized coordinates descending (OCD), were developed in response to these issues. Shahabuddin et al. [33] employed the MIMO networks for the small-scale businesses for efficient MIMO detection. In this research, they analyses matrix breakdown strategies for these systems. For M-MIMO arrangements they have presented the computationally demanding nature of nonlinear detecting strategies based on QR, Cholesky, and LDL decomposition methods. They contrasted them with the most advanced huge MIMO identification methods based on approximation inversion.

Yang et al. [34] offered an iterative identification approach that uses training from deep artificial neural networks (DNNs). Using the potent data produced by DNNs, we first present a constrained optimization-based technique for efficiently detecting repetitive soft output data. They suggested a way to alter the method's iteration variables, which provides great resilience and quick resolution. Sulttan [35] proposed an iterative decode approaches have contributed to the reduction of complication and enhancement efficiency (e.g. BER) in a variety of electronic communication networks over the past decade. The primary technology for improving and achieving large-speed, rapid data transfer, enhanced dependability, and penetration in mobile communications are MIMO methods. Low complication systems are needed for detecting in contemporary mobile phone networks since excessive computation by the CPU consumes more electrical power and reduces mobile adaptability. Seethaler and Bolcskei [36] proposed a cost savings come from a decrease in the semiconductor area needed for metrics computing and the circuit's critical pathway length, but they also follow from a decrease in computing difficulty via IND based designs integration to Sphere-Decoding (SD),

Liu et al. [37] proposed a solution to the single-input multi-output (SIMO) characterization for underwater optical wireless communication (UOWC) to prevent deep discoloration, Berceanu et al. [38] proposed downlink MIMO-OFDM technology described in this research uses its assets to satisfy the needs of multiple concurrently engaged users. A MMSE sensor is used at the customer service, and then a SIC is used for noise reduction. Demir and Björnson [39] address one-bit quantized and generalized additive equipment defects in huge multiple-input multiple-output (MIMO) devices for the detection of signals. Firstly, they introduce the generalized linear transmitters built around Bussgang breakdown and quantization-unawareness for the device impairments model under consideration. Chataut and Akl [40] have focused on enormous MIMO systems and provide an extensive review of the essential technologies that are needed for both 5G and 6G systems within this article. In addition to discussing some cutting-edge mitigation methods, we cover all the basic problems with contamination of pilots, channels estimating, coding, client planning, energy conservation, and signals identification in an enormous MIMO system. Tiba and Zhang [41] have gone beyond the restrictions and presented two deep neural networks (DNN)-based sensors in this operate: (1) to achieve greater efficiency, we create a DNN design that can effectively approximate adjustable punishment settings. (2) Without actually calculating the ADMM parameter revisions, they build a sub-DNN structure that is capable of estimating them. Zhang et al. [42] have recently worked on dense direction-of-arrival (DOA) estimates for MIMO radar, particularly on an approach that utilizes the traditional lowest absolute shrinking and selection operator (LASSO) estimate. Although it adds a new user variable, the alternating-direction approach to multiplication (ADMM) is a useful technique for resolving this issue.

The main difficulty of the selection and investigation of appropriate M-MIMO detection algorithms is to minimize the system's BER. It is sometimes necessary to utilize a rapid but efficient detection approach, particularly in real-time broadband applications. As a result, this research addressed the issue of underestimating the effectiveness of lineal detection algorithms considering their execution times.

4. MIMO DETECTION METHODOLOGIES

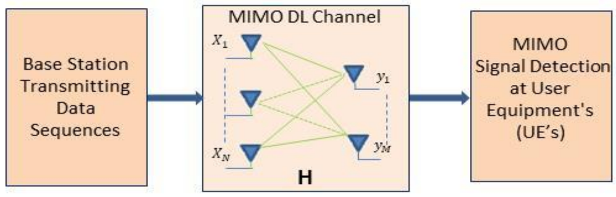
The paper discusses M-MIMO framework assuming a user terminal having M_T multiple antennas is served by a BS having M_R antenna arrays, where, $M_R > M_T$. Assumed to be taken from a set Sc in a rectangle M-QAM\PSK complex symbols in which q as a positive integer q=$\log_2$(M), is a transmission symbols vector S. The received signal matrix y, which is complex, may then be expressed as:

$$y = Hs + v \tag{1}$$

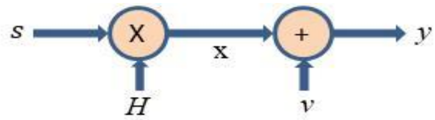
where, y$\in C^{M_R}$ is the signal matrix received, x$\in C^{M_T}$ is the transmitted input matrix, H$\in C^{M_R x M_T}$ is the channel state info matrix (CSI), and $v \in C^{M_R x M_T}$ is the additive AWGN noise. Data transmitted over noiseless channels may be defined as the:

$$x = Hs \tag{2}$$

System representation of M-MIMO DL and mathematical signal flow is represented in Figure 3. It is clear from the Figure that our prime concern is to model the MIM with larger BS antennas and highly dense users in the network considering beyond 6G scenario.



(a) MIMO DL system model



(b) Mathematical MIMO signal flow diagram

Figure 3. Channel formation process for the M-MIMO DL system

The challenge of current detectors is to receive the vector $(y - Hx)$ free of distortions and channel noise. Several equalizers or detection techniques were previously suggested. Nonlinear detectors are quicker than linear detectors, which are the most widely used. This report presents a comparison of these detectors.

4.1 Maximum likelihood detector (MLD)

Mathematical representation to given channel may be provided via MLD as:

$$\widetilde{x_{ML}} = arg \min_{x \in X^{(N_t,1)}} \|y - Hs\|^2 \tag{3}$$

where, $X^{(N_t,1)}$ represents the used integer numbers of transmitted symbols for M levels of PSK\QAM constellations orders. In the ML solution message s is chosen that minimizes the distance among the received signal as well as the hypothesized noise-free transmission Hs. However, their computing complexity in N_t is exponential in nature, making it exceedingly costly whenever the number of antennas gets massive.

4.2 Matching Filter (MF)

The MF interprets interference from different sub-streams as only noise when A=H is set. The estimated amount of received signal using MF is provided by:

$$x_{MF}=H^h y \quad (4)$$

where,

$$H^h = A = (H^h H)^{-1} H^h \quad (5)$$

However, when compared to more advanced detectors, MF performs worst for a large number of users.

4.3 MMSE detector

A most recently developed modulation scheme uses a minimum mean square error (MMSE) MIMO detector with low complexity. It is the linear detector algorithm that is used most often. By using MMSE detection, the Bayesian estimator in the continuous linear detection mechanism can be employed to improve efficiency [3]. It is expressed numerically as follows:

$$E\left({}^{x}/_{y}\right) = \left(H\,H^h + \left(\frac{\sigma^2}{\mathrm{E_x}}\right)\mathrm{I}\right)^{-1}(H^h y) \quad (6)$$

where, $\mathrm{E_x}$ indicate energy of transmitted symbols' enlargement. Consequently, the MMSE reduction problem is written as:

$$\widetilde{\mathrm{x_{MMSE}}} = arg \min_{a \in x^m} \left\| E\left({}^{x}/_{y}\right)_i - x \right\|^2 \quad (7)$$

The MMSE algorithm is considered to be the fastest amongst all linear detectors.

4.4 Gauss-Seidel (GS)

The linear channel problem (as defined in Eq. (1)) must be solved using the Gauss-Seidel (GS) algorithm, often known as the sequential displacement approach. The equalization matrix A is sub divided by the GS technique into three components: a diagonal matrix (D), a matrix with an upper triangular shape U_t, along with the lower triangular matrix L_t, with the formula being A=D+U_t+L_t. Where the actual matrix A is given as:

$$A = \left(H\,H^h + \left(\frac{N_0}{\mathrm{E_x}}\right) I_U\right) \quad (8)$$

The D is a diagonal matrix and is represented as:

$$D = diag(A) = \begin{bmatrix} A_{11} & & \\ & A_{22} & \\ & & A_{NN} \end{bmatrix} \quad (9)$$

If proper initialization is taken into account, the GS technique converges swiftly. The GS algorithm's predicted signal is expressed as:

$$X_n^h = (D - L_t)^{-1}(y_{MF} + X_{n-1}^h U_t) \quad (10)$$

4.5 Conjugate Gradient (CG) detector

The conjugate gradients (CG) technique offers another approach for solving linear equations with n iterations. The signal generated by the CG method is denoted as:

$$X^{h(n+1)} = X^{h^n} + \alpha^n p^n \quad (11)$$

where,

$$\alpha^n = norm(p)^2/(p' Ap) \quad (12)$$

where, the exponent matrix product is defined as:

$$e = Ap \quad (13)$$

4.6 Neumann Approximation Series (NAS)

Neumann series (NS) based solution is well suited for huge MIMO systems; the NS has been suggested for carrying out a Matrix Inversion Approximation (MIA). The NS expansion is used to simulate the inversion of matrix using an array of matrices-vector multiplications, that are cheap to implement using hardware but has a delayed convergence. An iterative approximation of the K-term Neumann series, as matrix inversion solution, is defined as follows:

$$A_n^{-1} = A_{n-1}^{-1} + (-(D^{-1}L_t)^{itr} * D^{-1}) \quad (14)$$

The final solution is given as:

$$X^h = A^{-1} H^h * y \quad (15)$$

The time and BER performance of the NS based methods are questionable.

5. DESIGN OF ITERATIVE ADMM-BASED IND

The IND is a well-known box-constrained MIMO detector [31-35]. An optimization algorithm called ADMM breaks down complex problems into simpler sub problems that are easier to tackle.

The optimization problem is defined as:

$$\min_{s.t.\ X\ \in\ C} f(x) \quad (16)$$

With a $X€R^n$ the convex optimization problem can be written as ADMM form as:

$$\text{for } X = Z \min_{X\ \in\ C}[f(x) + g_{IF}(z)] \quad (17)$$

where, g_{IF} is indicator function? The suggested detector with an IND (∞-norm) basis makes use of the complex valued vector x's component-wise ∞-norm. IND aims to maximize the solution values as:

$$\|x\|_{\infty}\tilde{} = \max_i \left[\max_i [H(xi), y(xi)]\right] \quad (18)$$

The BOX constrain is considered for IND as $\|x\|_\infty \leq \rho$ with box of length 2 ρ. This box constrain allows reducing the problem, to convex optimization as:

$$\tilde{x}_{Box} = \arg \min_{x \in RC_O^i} \|y - Hx\|_N^M \tag{19}$$

where, RC_O^i , is reduced constellation order of i[th] QAM symbol (S_i). Thus the Eq. (17) can be re modified as:

$$\tilde{x}_{Box} = \arg \min_{x \in RC_O^i} (\frac{1}{2}(y - Hx)_N^M + g_{IF}(z)) \text{ s,t, } \quad x = z \tag{20}$$

Expand the Eq. (20) using augmented Lagrangian expansion gives:

$$\mathcal{L}_\beta(\mathrm{x,z,\lambda}) = \frac{1}{2}(y - Hx)_N^M + g_{IF}(z) + \frac{\beta}{2}[z - x - \lambda]_M^M \tag{21}$$

Taking derivative and equating Eq. (21) to zero gives the solution of ADMM optimal augmented Lagrangian solution for x and z as:

$$H^h(y - Hx) - \beta(z - x - \lambda) = 0$$

Which leads to x solution.

$$\tilde{x} = [G^{-1}(x_{MF} + \beta(z - \lambda))] \tag{22}$$

where, $G = H^h H + \beta.I$ and the variable x_{MF} is matched filter represented as x_{MF}=H'y. it is to note that initializing $z = \lambda = 0$ may leads to MMSE inital solution.

This paper proposed to use the energy scaling concept based on iteratively updating the variables associated with Monte Carlo simulation for enhancing the performance of the existing ADMIN based MIMO detection methods. A well-known numerical method for addressing a broad range of constrained convex and non-convex optimization issues is the ADMM methodology [12]. It functions by dividing the initial convex optimization challenges into smaller, more manageable vector problems.

ADMM solves the optimization problem as given in (20) for communication systems using the comparable Algorithm 1: the major advantage of ADMIN is its speed of convergence and efficiency at higher SNR level. In this paper, an efficient concept of reduced constellation order (RCO) is proposed for Massive MIMO along with proposed modified iterative ADMIN detectors. These all modifications may offer use of ADMIN detectors at low and high SNR values too. The energy is scaled 3 times and titration count itr_L is scaled to 5.

The IND is iterated until a stopping requirement is satisfied the ADMM algorithm modifies the estimation of the sent symbols every iteration, depending on the received signals and limitations The suggested approach founded on ADMM and IND has several advantages, including increased dependability, improved spectrum efficiency (SE) and EE, improved geographical variety, and more.

Algorithm 1. Modified Tweaked ADMM based IND Detector: ADMIN

Inputs: ← received vector y, CSI matrix H, noise estimate N_0 and energy E_s
1: Generate initial MMSE estimate
2: β=$N_0 E_s{}^{-1}$s ← set energy tweaking scale as 3 fold for improvement
3: G=H[h] H+β I_U
4: G=L d L H
5: L˜=L−1, D˜=D−1
6: Initialization of loop parameters
7: z=0 ;
8: λ=0 and solve for
9: x_{MF}=H'y: as matched filter estimate
10. Iterate over Detection loop
11: for i=1:1: itr_L ↑ have scaled up to 5
12: x˄←L[t] H D[t] L[t] (x_{MF}+β(z−λ))
13: Update z as: z˄←projCO (x˄+λ, α)
14: λ←λ−γ(z^h−x^h)
15: z←z^h
16: end
17: output: x^h

Additionally, the proposed system seeks to overcome the limitations of hardware cost, energy usage, as well as signal detection-related difficulties, particularly when massive antennas are used.

6. POWER ADAPTIVE NOMA-MIMO WITH ADMM DETECTION

The paper proposed to investigate the error rates for different MIMO sizes and for different constellation orders of M-QAM. The MIMO channel damnations are varied by changing the Nr and Nt for different MIMO structures. In this work the concept of the MIMO is extended to the integration of the NOMA concept with the basic two user concept. The system diagram of the NOMA-Massive MIMO with adaptive power allocation is shown in Figure 4.

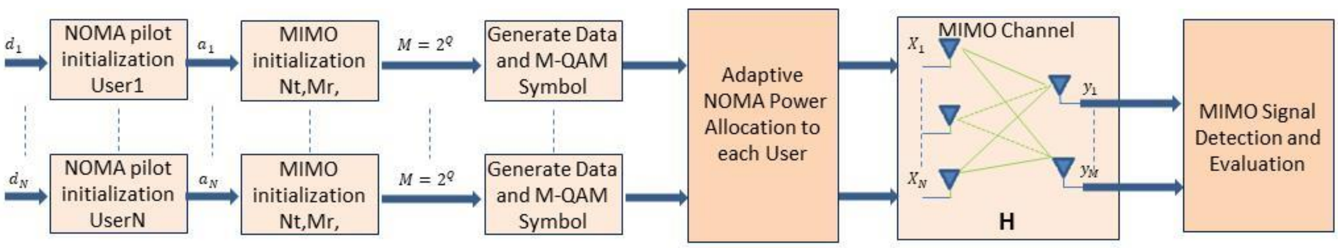


Figure 4. Proposed NOMA-Massive MIMO system with adaptive power allocation

6.1 Adaptive power allocation

In this paper, it is proposed to adopt the power levels of the NOMA user in proportion to the distance of the user from BS. The initial power level allocation and the user distance vectors are defined as:

$$d = [d_1, d_2 \ldots\ldots d_n] \text{ and } a = [a_1, a_2 \ldots\ldots a_n] \tag{23}$$

where, d is the distance vector of NOMA users from BS; and a is the power scaling vector and n is the number of users in the network connected to BS. The paper proposed to adopt the power using the power allocation theorem in order to improve the energy efficiency of NOMA users.

Theorem 1:
The optimal power allocation is achieved in NOMA system when the power scaling factor a of each user is adopted in theorem total sum of the distance scaling factor d as:

$$T = \sum_{J=1}^{n} d_j/1000 \tag{24}$$

When j is assigned that distance vector d_j is defined in term of n as the number of users. Then, power scaling ratio for NOMA user is calculated as:

$$a = \underbrace{\in}_{d=1,n} d_j/T * 1000 \tag{25}$$

Justification: Using Theorem 1 it is proposed to allocate main power to every distant NOMA user in proportion to distance vector from BS. This will allow closer users to use less power and distant user to use more power and offers EE solution to the system.

For example for two users with random distance vector d=[1000, 50000] the power algorithm factor $a = [\frac{1}{6}\ \frac{5}{6}]$ respectively. The power adoption Algorithm is given in Algorithm 2; The flow chart of the proposed NOMA-M-MIMO methodology using the modified iterative ADMIN detector is given in Figure 5. The number of Monte Carlo simulations and the ADMIN loop iteration are adopted optimally for performance enhancement.

Algorithm 2. NOMA Power Adoption

1: Inputs: ← number of input users N, vector d, vector a,
2: Define random distance vector d and initial power factor vector a using Eq. (23).
3: Calculate threshold ← T using the Eq. (24)
4: estimate the optimal power allocation per user using Eq. (25) as:

$$a = \underbrace{\in}_{d=1,n} d_j/T * 1000$$

5: Calculate the Sum Rate SR for evaluation
6: end Algorithm

In order to justify the power allocation effectiveness, the sum rates (SR) are calculated and plotted for the radon distance vectors. The standard description of various QAM symbols used for modeling is shown in Table 2. It is clear from Table 2 that order of modulation is used to adopt the symbol vectors.

Experimental Setup: The proposed M-MIMO system is simulated using the MATLAB environment. The MIMO signal x and channel realization information H is randomly generated. The simulation parameters used for modeling NOMA-M-MIMO system are shown in Table 3. The optimal selection of number of antennas at the transmitter and receiver is used for simulations and the tweaked parameter is set to 3.

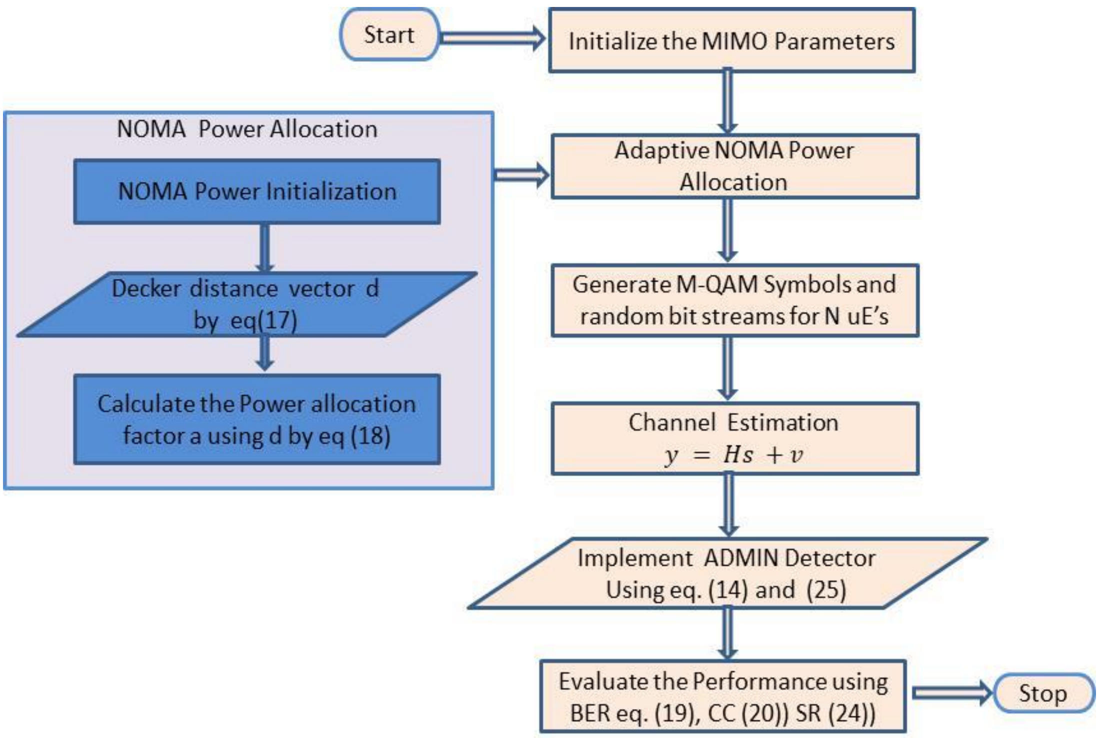


Figure 5. Flow chart of the proposed evaluation

Table 2. Description of M-QAM symbols (de Sousa et al. [43] and reference [44])

Order of QAM	Symbols Used
2	[-1 1]
4	[-1 -1i, -1+1i, 1-1i, +1+1i]
16	[-3-3i,-3-1i,-3+3i,-3+1i,-1-3i,-1-1i,-1+3i,-1+1i,+3-3i,+3-1i,+3+3i,+3+1i,+1-3i,+1-1i,+1+3i,+1+1i];
64	[-7-7i,-7-5i,-7-1i,-7-3i,-7+7i,-7+5i,-7+1i,-7+3i,-5-7i,-5-5i,-5-1i,-5-3i,-5+7i,-5+5i,-5+1i,-5+3i,-1-7i,-1-5i,-1-1i,-1-3i,-1+7i,-1+5i,-1+1i,-1+3i,-3-7i,-3-5i,-3-1i,-3-3i,-3+7i,-3+5i,-3+1i,-3+3i,+7-7i,+7-5i,+7-1i,+7-3i,+7+7i,+7+5i,+7+1i,+7+3i,5-7i,+5-5i,+5-1i,+5 3i,+5+7i,+5+5i,+5+1i,+5+3i,++1-7i,+1-5i,+1-1i,+1-i,+1+7i,+1+5i,+1+1i,+1+3i,+3-7i,+3-5i,+3-1i,+3-3i,+3+7i,+3+5i,+3+1i,+3+3i]

Table 3. Simulation and optimization parameters used for experiments

Parameter	Description	Range/Value
d	Distances of NOMA users from nearest BS	d=[10 100]m
a	Power allocation factors of NOMA users from BS	a=[0.3 0.7]
eta	Path loss exponent	Set to 1
Pt	Transmitting power in dB	Pt=1:30
BW	MIMO System Bandwidth	BW=10^6
N_o	Noise power in dB scale	$N_o = -174 + 10 * log10(BW)$
N_R	Number of MIMO receive antennas	$N_R = [4, 8, 16, 32, 64]$
N_T	Number of MIMO transmitting antennas	$N_T = [4, 8, 16, 32, 64]$
trials	Number of MC iterations	Trials=10000 or 100000
detectors	Type of MIMO detectors used	MF, CG, GS, NSA, ADMIM
Q	Number if Bits used per-symbol	Q=log2(length(symbols)
C_{MIMO} (K)	Channel capacity of kth SNR for MIMO channel	- -
tweaked	Parameter to be used for modified ADMIM	Tweaked=[2 or 3]
beta	Pre-processing energy factor for AMIM initialization	$beta = (N_o/Es).tewaked$
Es	Network energy	Es=max(abs (symbol^2))

7. RESULT AND DISCUSSIONS

In this paper, experimentations have been performed for designing the high capacity efficient methodology considering the beyond 6G communication using MIMO detection technique. The paper considered BER, channel capacity, time, and sum rate as parameters for performance evaluation. The concept of MIMO is extended to NOMA-Massive MIMO and the various techniques of MIMO detections are considered for the equalizers at the detectors. In the design methodology, the highly massive beyond 6G huge 64 to 256 antennas transmitting structure is considered with large number dense receiver diversity 16 to 256 user's, antenna for MIMO system detection. The computation of a likelihood of error as well as the mathematically defined symbol error rates or BER is used to assess the MIMO system's effectiveness.

$$Pb_{MQAM} \approx \frac{4}{log_2 M}\, Q\left(\sqrt{\frac{3\,\gamma_b\, log_2 M}{M-1}}\right) \tag{26}$$

where, M is order of the modulation symbol and Q is the error function.

7.1 Validation of the massive MIMO detectors

The first experiment is performed to validate the existing BER performance of various mentioned Massive MIMO detectors in this paper. These MD includes CG, NAS, GS, and ADMIN detectors. The experimentation considered the normal user density of 16 and 32 users along with the 64 antennas at the BS transmitter at downlink. The ultimate goal is to evaluate the performance of box detection methods including ADMM detector. The huge beyond 6G massive 64 antenna structure was considered with the large number of receiver units. Figure 6 compares BER for 64QAM modulation system for these MIMO detections.

In order to examine the performance of the MIMO detection for the higher antenna sizes. The antenna at transmitting structure is kept to 64 and the BER is evaluated for the different numbers of the user units for the 64QAM MIMO architecture. Figure 6(a) and Figure 6(b) evaluated the BER for the MIMO detectors for 16 users and 32 users respectively.

It is observed that most of methods including GS, CG, and NAS failed to offer good BER performance but infinity norm detector ADMIN offers significant comparative performance and offers the minimum BER of the order of 3.1×10^{-4} for 64×16 at 20dB for case a) and 2.6×10^{-4} BER for the 24dB SNR for 64×32 antenna system/in case 2 of Figure 6. But still there is a significant chance of improvement in the performance. For statistical analysis the symbol error rate (SER) is calculated as;

$$SER = 1 - (1 - BER)^{N_{bps}} \tag{27}$$

For 64 QAM modulations, the bits per symbol $N_{bps} = 6$ and respectve SER is shown in Table 4.

The BER and SER comparative performance of various state of art MD methods for different MIMO sizes for validated approach are shown in Table 4. The BER is increased to nearly 100 times with decreasing user density from 64 to 16 users. Also, it is to be observed from Table 4 that, as the size of channel increases the SNR performance is also decreased and it requires higher SNR relatively. Thus, significant chance of performance enhancing is required for such detectors with the increasing capacity of channels.

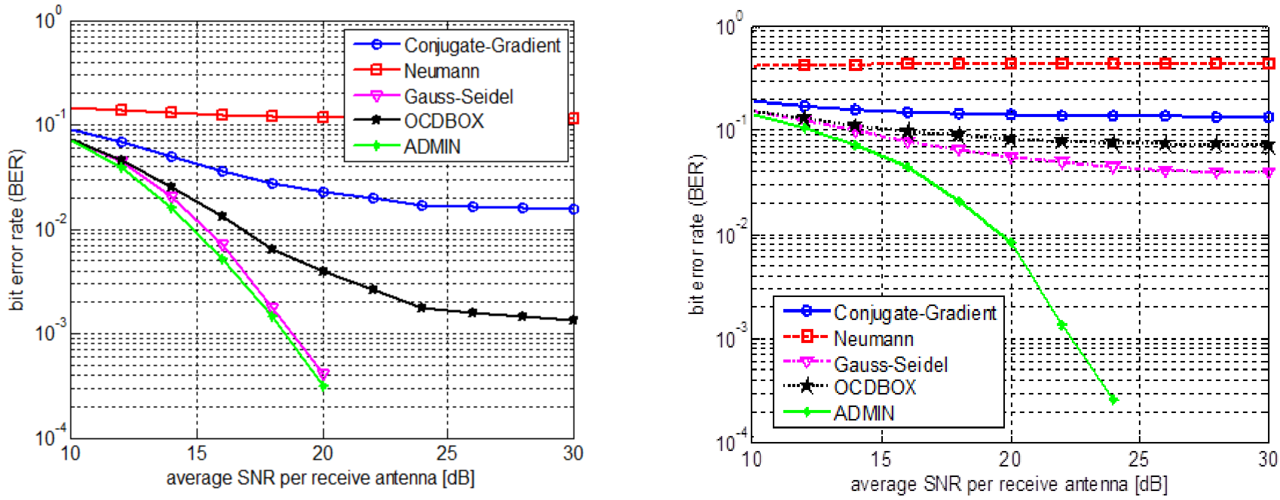
It is clear from Table 4 that ADMIN outperforms over other MIMO detectors. In order to statically signify the results, the t-test is carried out and the mean BER and SER are compared in Table 5 for four MD's respectively for 64×16, 64×32, and 64×64 MIMO sizes. It can be observed that ADMIM is capable of offering lower BER at even lower SNR values.

Table 4. Statistical comparison of various state of art MIMO detectors

Method	Parameters	64×16 MIMO	64×32 MIMO	64×64 MIMO	T-Test
CG	BER	1.8×10^{-2} at 30 dB	1.5×10^{-1} at 30 dB	2.8×10^{-1} at 30 dB	1.4933×10^{-1}
	SER	$10{,}325\times10^{-2}$ at 30 dB	$6.23\text{x}10^{-1}$ at 30 dB	8.6×10^{-1} at 30 dB	5.2875×10^{-1}
Neuman	BER	1×10^{-1} at 30 dB	4×10^{-1} at 30 dB	5×10^{-1} at 30 dB	3.337×10^{-1}
	SER	9.99×10^{-1} at 30 dB	9.96×10^{-1} at 30 dB	9.84×10^{-1} at30 dB	9.93×10^{-1}
GS	BER	4.1×10^{-4} at 20 dB	3.9×10^{-2} at 30 dB	2.7×10^{-1} at 30 dB	3.41366×10^{-2}
	SER	24.57×10^{-4} at 20 dB	$21{,}234\times10^{-2}$ at 30 dB	32.32×10^{-2} at 30 dB	18.67×10^{-2}
ADMIN	BER	3.1×10^{-4} at 20 dB	2.6×10^{-4} at 24 dB	6.1×10^{-2} at 30 dB	2.0523×10^{-2}
	SER	18.6×10^{-4} at 20 dB	15.59×10^{-4} at 24 dB	30.68×10^{-2} at 30 dB	10.340×10^{-2}

Table 5. Statistical t-test performance of parameters

Parameters	Neuman	CG	GS	ADMIN
BER	3.337×10^{-1}	1.4933×10^{-1}	3.41366×10^{-2}	2.0523×10^{-2}
SER	9.93×10^{-1}	5.2875×10^{-1}	18.67×10^{-2}	10.340×10^{-2}
SNR	30 dB	30 dB	26.66 dB	24.66 dB



(a) For 64 antennas and 16 users

(b) with 64 antennas and 32 users

Figure 6. Result of validation of the BER for various Massive MIMO detectors for 64QAM beyond 6G MIMO detections

It can be observed from Table 5 that ADMIM offers 1.6638 times the average BER improvement and 1.80560 times the average SER improvement over GS method at system SNR range of 20dB, the best performance is highlighted in red.

7.2 Massive MIMO detectors for large mobile units

The experiment offers to increase the number of MU's considering the large density in future communication system. The MU's is considered to be 64 for 64 BS antennas and BER is evaluated for the M-MIMO system. Performance for the Box based MIMO detectors and the relative comparison with other methods is presented in Figure 7.

The number of users is doubled to large 64 user's receiver units are considered for evaluation. With the existing ADMIN detector there is significant reduction in BER performance is observed in Figure 7. This Figure is clearly and statistically justified in Table 6.

The BER is validated first as random experiment for 64QAM and large 64×64 antennas at 30dB and comparative performance of minimum BER for various MD's are presented in Table 6. The BER is increased to the nearly 60 times with BER of 6.1×10^{-2} for proposed ADMIM method over OCDBOX for 64×64 antennas. It is also observed from Table 6 that ADMIM based detector offer 3.1297, 2.7724, 2.7346, 2.698 times improvement in SER over Neuman, CG, GS, and OCDBOX based approximation and box based MIMO detectors respectively.

7.3 Iterative Monte Carlo evaluation under RCO adaption

The paper considered the conventional detectors as MF and MMSE detectors. The approximate inversion based detection (AID) which uses approximation algorithms like Neumann-series approximation, Gauss-Seidel, and conjugate-gradient approaches. Thus in this experiment, the number of BS antennas is reduced and the respectively the number of users is also considered to be reduced which corresponds to the reduced constellation order of the M-QAM system. This RCO concept is adopted for performance improvement.

Table 6. Minimum BER for various MD's for 64QAM and large 64×64 antennas at 30dB

Method	Neuman	CG	GS	OCDBOX	ADMIN
BER	5.0×10^{-1}	2.9×10^{-1}	2.8×10^{-1}	2.7×10^{-1}	6.1×10^{-2}
SER	9.84375×10^{-1}	8.7189×10^{-1}	8.601×10^{-1}	8.486×10^{-1}	3.14522×10^{-1}

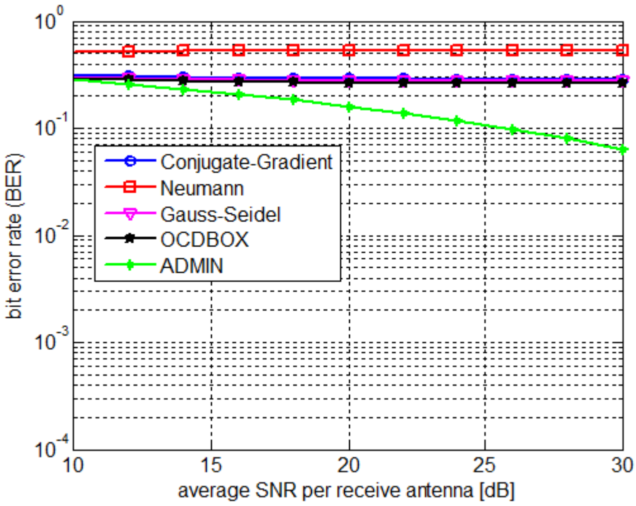


Figure 7. BER of Massive MIMO detectors for 64QAM and large 64 user units

The BER of 8 different M-MIMO detectors are compared for the RCO concept for 16 QAM in Figure 8 it can be observed that for this case the ADMIN method detector out performs over other methods. Nearly the BER of the order of 10^{-4} is achieved from the infinity norm detector. The 32×16 antenna architecture is adopted for the MIMO under evaluation in this experiment. The best performance of BER in Figure 8 is offered for the SIMO system. It is obvious due to less size of channel, but for the MIMO size, the ADMIN detector has edge over others.

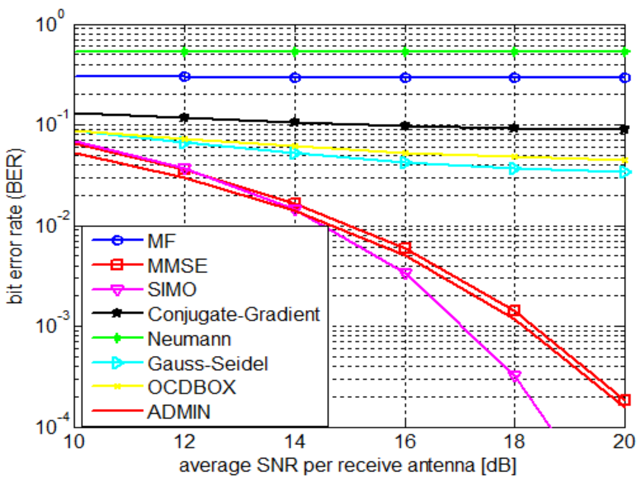


Figure 8. BER of M-MIMO detectors for 32 receive antennas and 16 UT with RCO set to 16 QAM modulations

7.3.1 Iterative MC simulation

The concept is extended to the Monte Carlo (MC) simulation the number of iterations is increased to 100 times. And the energy scaling is set to 1 but the ADMIN loop count is set to 5 instead of 3. It is observed that the proposed modifications have made the significant improvement in the optimal performance of the MIMO detections.

The results of M-MIMO detectors for 16 receiver antennas and 16 UE are evaluated and plotted the BER performance based on different RCO as shown in Figure 9. It can be observed that RCO with BPSK and QPSK offers the minimum BER performance but at the lower SNR values. For the performance of reduced order (RCO) modulations BER of the order of 10^{-4} is achieved with the QPSK at the 25dB SNR range.

It is also clear from Figure 9 that at the relatively higher SNR range the 16 QAM gives the nearly 10 times good performance than 64 QAM and is proposed to be preferred beyond 5dB SNR.

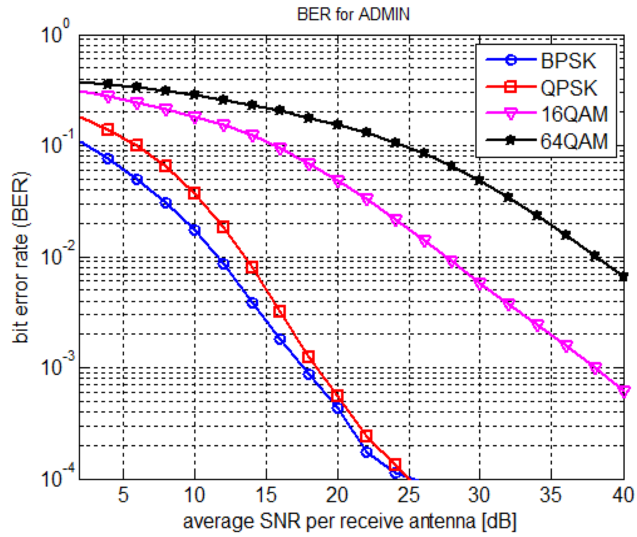


Figure 9. Result of M-MIMO detectors for 16 receive antennas and 16 UT BER performance based on different RCO

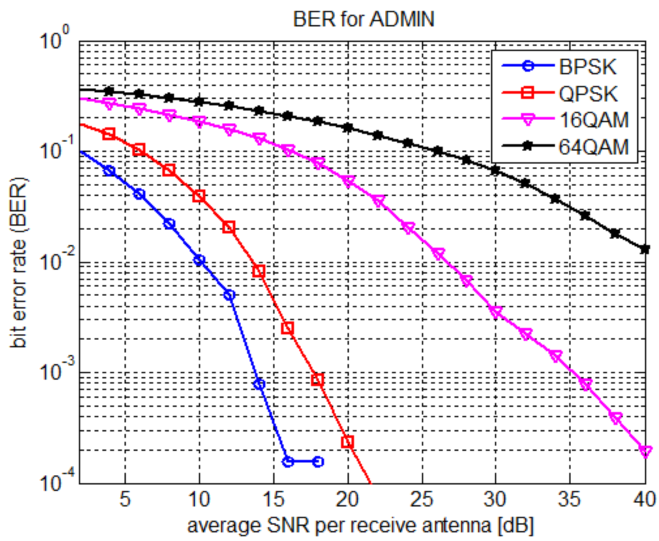


Figure 10. Impact of RCO based modulation over the Massive MIMO performance for 64 BS antennas and 16 UEs for different order modulations

As another experiment the impact of RCO based modulation over the Massive MIMO performance for 64 BS antennas and 16 UEs for different order modulations are evaluated in Figure 10 it can be observed that with the proposed iterative approach still increasing the antenna size may offer the BER of the order of 10^{-4} or QPSK at 21 dB SNR only with 4dB better SNR performance than the previous case of 16 antennas.

7.4 Optimal iterative hybrid massive MIMO detection

The proposed method of MD has used the hybrid combination of the MMSE and the ADMIN based iterative detector. The combination may offer improved BER performance. The number of MC iterations is set to 10000 and the admin loop count is set to 5. In this experiment, the massive MIMO size is selected to be 64 BS antennas with 64 users. Thus the channel is of H size of 64×64.

The simulation is carried out for the ADMIN based iterative detector only but for four modulation methods. As BPSK, QPSK, 16 QAM and 64 QAM.

It is observed from Figure 11 that seven for the higher MIMO dimensions and large user density the proposed method with QPSK modulation offers significant BER performance and that to at lower SNR values of 26dB. The minimum BER of the 7.4×10^{-7} is achieved for the proposed MIMO detector. This is a significant improvement over the existing validation results by the order of nearly 500 times.

The results of the proposed hybrid detectors with the impact of RCO based optimal iterative Hybrid ADMIN detector over the massive MIMO performance for 128 BS antennas and 128 users, for different modulations are shown in Figure 12. The BER of the order of the 7.6×10^{-7} is offered at the 4 dB lesser then the 64×64 antenna case for QPSK. A similar simulation is run to evaluate the BER performance of the Hybrid ADMIN detector for massive MIMO with 256 BS antennas and 256 users for different modulations as shown in Figure 13.

The statistical comparison of Figures 9 to 13 for BER with MC simulation for different modulations for the proposed modified ADMIM detector is given in Table 7.

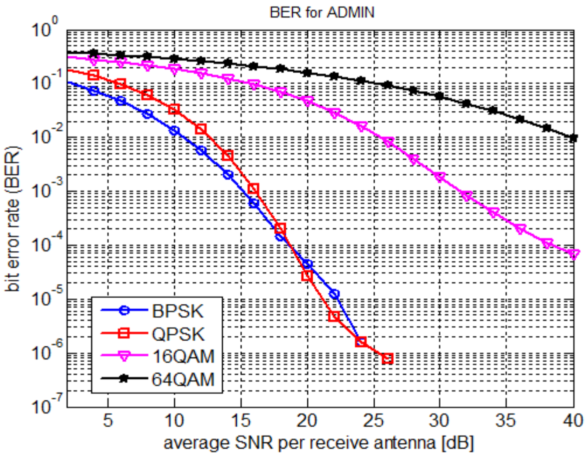


Figure 11. Impact of RCO based optimal iterative Hybrid ADMIN detector over the massive MIMO performance for 64 BS antennas and different order modulations

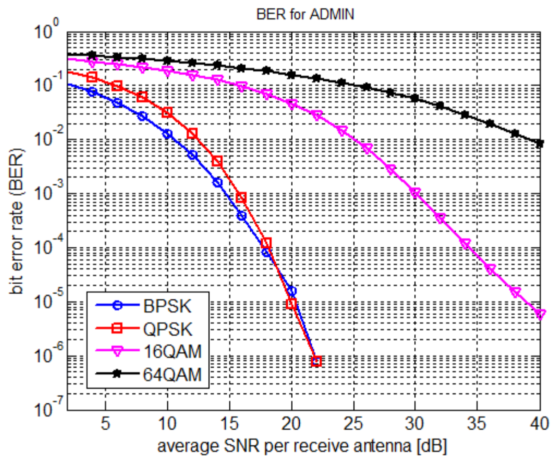


Figure 12. Results of the BER based on optimal iterative Hybrid ADMIN detector for massive MIMO with 128 BS antennas and 128 users for different modulations

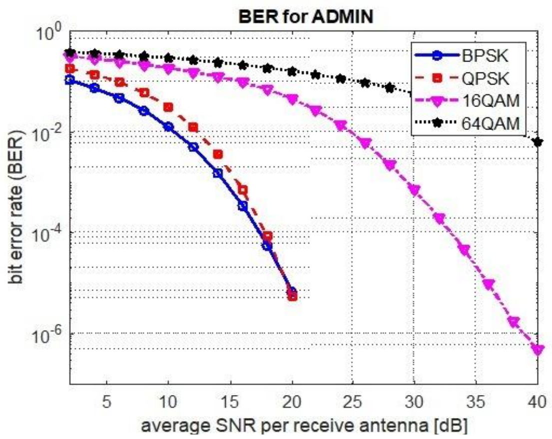


Figure 13. Results of the BER for Hybrid ADMIN detector for massive MIMO with 256 BS antennas and 256 users for different modulations

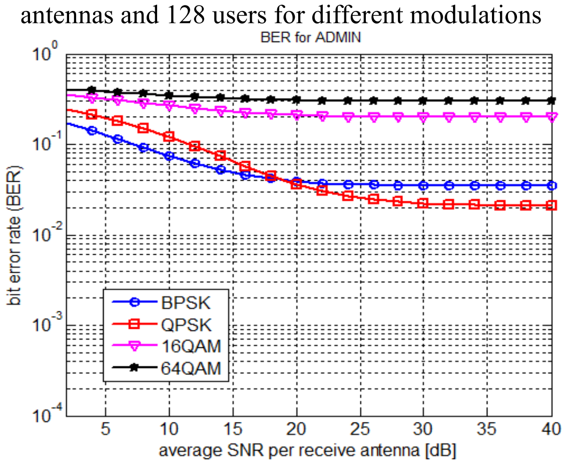


Figure 14. BER for Hybrid ADMIN detector for massive MIMO with 80 BS antennas and 120 users

Table 7. Statistical comparison of BER/SER for MC simulation based various RCO modulations

Method	Parameters	16×16 MIMO Itr=1000	64×16 MIMO Itr=1000	64×64 MIMO Itr=10000	128×128 MIMO Itr=10000	256×256 MIMO Itr=10000	t-test
BER	BPSK	1×10^{-4} at 24dB	1.5×10^{-4} at 18dB	2×10^{-6} at 24dB	1.8×10^{-5} at 20dB	8×10^{-5} at 20dB	7×10^{-5}
	QPSK	1×10^{-4} at 24.8dB	1×10^{-4} at 21dB	7×10^{-7} at 26dB	3.1×10^{-7} at 22dB	7×10^{-5}at 20dB	5.4×10^{-5}
	16QAM	6.1×10^{-4} at 40dB	2×10^{-4} at 40dB	7.1×10^{-5} at 40dB	4×10^{-6} at 40dB	6.4×10^{-7}at 40dB	1.8×10^{-4}
	64QAM	5.8×10^{-3} at 40dB	1.2×10^{-2} at 40dB	1×10^{-2} at 40dB	7.2×10^{-3} at 40dB	8.2×10^{-3} at 40dB	8.6×10^{-3}
SER	BPSK	5.99×10^{-4} at 24dB	9.8×10^{-4} at 18dB	11.9×10^{-6} at 24dB	1.07×10^{-2}at20dB	47.9×10^{-5}at 20dB	42×10^{-5}
	QPSK	5.6×10^{-4} at 24.8dB	5.6×10^{-4} at 21dB	42×10^{-7} at 26dB	18.4×10^{-7}at22dB	42.4×10^{-5}at 20dB	32.4×10^{-5}
	16QAM	36×10^{-4} at 40dB	11.9×10^{-4}at40dB	42×10^{-5} at 40dB	23.8×10^{-6}at40dB	38.4×10^{-7}at 40dB	10.8×10^{-4}
	64QAM	34.3×10^{-3} at40dB	7.2×10^{-2} at 40dB	5.8×10^{-2} at 40dB	4.24×10^{-2} at40dB	49.2×10^{-3}at 40dB	51.6×10^{-3}

It can be observed from Figure 13 that at the worst case of massive MIMO dimension of 256×256 the QPSK offers minimum BER at 20 dB value which is 2dB less. And it is also clear that as the massive MIMO dimensions improved the 16 QAM performances have significantly achieved the better BER of the order of 10^{-7} but at the slightly higher SNR range.

The statistical performance is evaluated for the MC based modified ADMIM detector for different modulation orders for different MIMO sizes as given in Table 7. In this paper, it is proposed to increase the MC iterative count as the MIMO size is increased. The iter=10000 is used for simulations.

It is concluded that using the adaptive concept of RCO along with MC simulation can significantly minimize the NER at massive MIMO sizes of 64×64, 128×128, and 256×256. The best MIMO performance with RCO-MC is achieved for QPSK as 3.1×10^{-7} at 22dB for 128×128 and 7×10^{-7} at 26dB for 64×64 antennas. It is also observed from Table 7 that as the size of MIMO increases more signal is assumed over the channel thus minimum BER is achieved at lower SNR values.

A final experiment has plotted the BER for Hybrid ADMIN detector for massive MIMO with 80 BS antennas and 120 users in Figure 14. However, in practice, the order of two is recommended for better performance as MIMO antenna sizes.

7.4.1 Comprehensive performance comparison

A more comprehensive methods considered under the literature review are compared based on the minimum BER performance achieved by them. The comparisons of BER for seven MIMO detectors including proposed method case are tabulated in the Table 8. It can be clearly observed that proposed MC simulation based RCO ADMIM method with QPSK modulation offers the best minimum performance for 64×64 antennas 7×10^{-7} at 26 dB only and for 128×128 systems 3.1×10^{-7} at 22 dB as best performance.

Table 8. Comprehensive comparison of MIMO detectors with proposed method

Methods Parameters	**SOR MD with 128×16 MIMO Divya et al. [14]**	**BOXBCD 16 QAM 100×100 MIMO Quan et al. [1]**	**OSIC MD with 16 QAM 4x4 MIMO Praveena et al. [13]**	**CD-SOR 128×32 MIMO 64QAM Labed and Aounallah [23]**	**Neumann Series Iterative 256×32 MIMO Shao and Zu [30]**	**Proposed MC-RCO-QPSK with 64×64 MIMO**	**Proposed MC-RCO-QPSK with 128×128 MIMO**
Min BER	1×10^{-4} at 21dB	1.5×10^{-5} at 28dB	1×10^{-5} at 16dB	6.1×10^{-5} at 20dB	7.5×10^{-5} at 30dB	7×10^{-7} at 26dB	3.1×10^{-7} at 22dB

7.5 Evaluation of the channel capacity

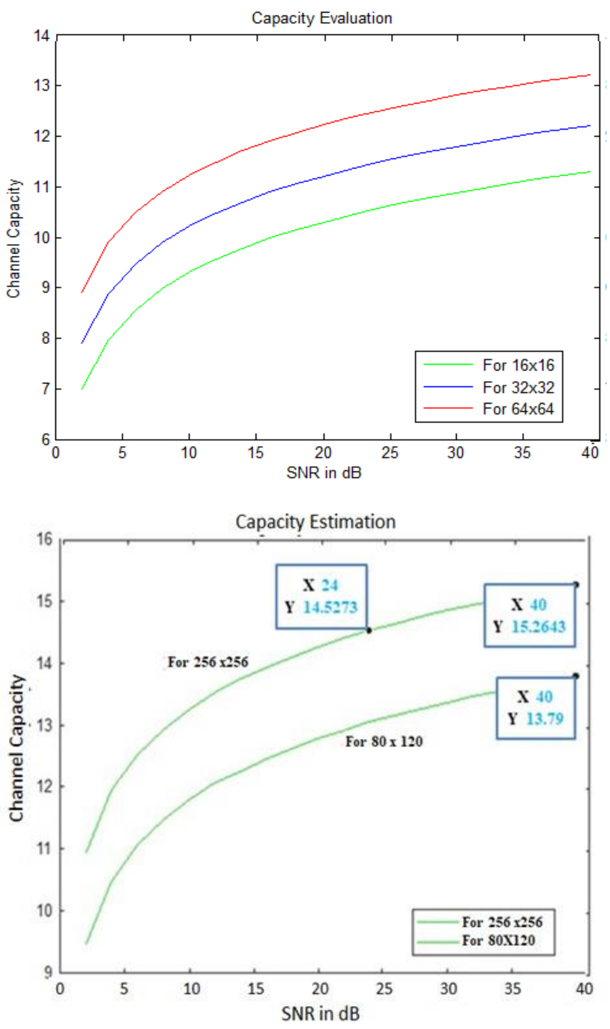


Figure 15. Channel capacity of the massive MIMO system

The channel capacity is primarily the measure of the range of information to be sent over the any communication channel. The capacity in terms of CSI is calculated and defined here as in Eq. (28):

$$C_{MIMO} = \sum_{k=1}^{L_{SNR}} C(K) + log_2(1 + SNR(K) * norm(H)^2) \tag{28}$$

where, for k=1 the $C(K) + is\ set\ to\ 0\ initially$, the capacity of the massive MIMO channels are evaluated for the different size of MIMO antennas. The Channel size is varied to 16×16, 32×32, 64×64, 128×128 and 256×256 for the capacity measurement experiment. Figure 15 has plotted the capacity comparison and improvement using the massive MIMO of the system. It can be observed that as the size of H increases the capacity of system increases.

The justification of Figure 15 for the channel capacity valuation is given in Table 9 for the maximum offered capacity at 40dB SNR range. It is clear from the Figure that increasing mMIMO size may exponentially increase the channel capacity of the communication systems. A comparison of the maximum capacity and improvement for MIMO sizes is given in Table 9. The exponential increase with the size of MIMO is observed in Table 9.

Table 9. Comparison of the maximum capacity and improvement for MIMO sizes

Parameter\Size	**For 16×16**	**For 64×64**	**For 128×128**	**For 256×256**
Capacity	10.61	13.13	13.79	15.2443

7.6 NOMA-MIMO evaluation

The NOMA power allocation performance is measured and accessed in terms of Sum Rate (SR) of the NOMA-M-MIMO system in this section. In order to calculate the Sum rate following initial estimates and coefficients are defined in the system. The gains of the channels for the two NOMA users are defined in terms of channels matrix H_1 and H_2 respectively as:

$$g_{1,2} = abs\ (H_1 : H_2)^2 \tag{29}$$

The NOMA parameters used for SR calculations are defined in Table 10. Initially, the signal and noise power densities are defined as given in Table 10 the SR is calculated.

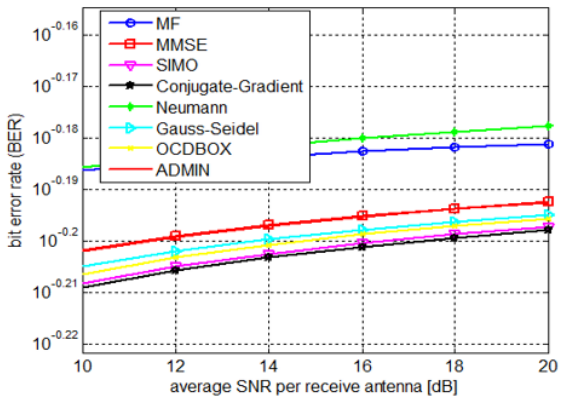
The Algorithm for the Sum Rate SR calculation is given in Algorithm 3. The simple and systematic calculation process is clearly mentioned in the Algorithm.

The BER performance of the two users NOMA combined with the Massive MIMO system for 64×16 systems are plotted in Figure 16. It is clear that there is tremendous room for improvement in the BER performance of such high-end information systems.

The sum rates are calculated and evaluated to show the performance of the powered allocation in the NOMA system. Figure 17 represents the SR evaluation for the three different random distance vectors and the power allocation is adopted accordingly to produce the channel realization.

Table 10. The NOMA parameters used for SR evaluation

Parameter	Range	Relative Measures
Target rate R1	Set to 1	--
Targeted % SINR ϵ	$(2^{R1}) - 1$	--
Power range P_t	0-30	$pt = 10^{-3}db2pow(P_t)$
Noise level N_0	-114	$n0 = 10^{-3}db2pow(N_0)$



For 64×16 antennas

Figure 16. Result of the NOMA-MIMO detection with ADMIN performance for the 64×16

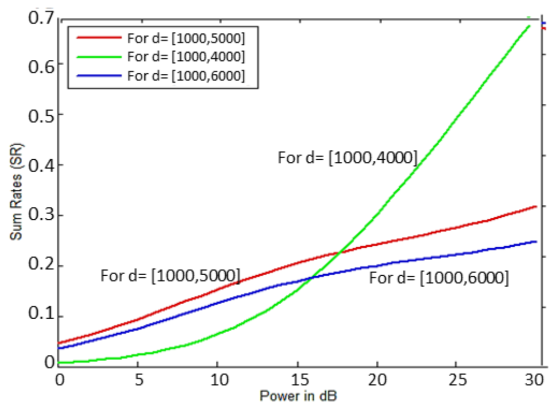


Figure 17. Evaluations of the NOMA sum rates for the three different random distance vectors

Algorithm 3. NOMA SR Calculation

1. Loop over the power range
   for u=1:1:L_{P_t}

$$\beta_1 = \epsilon\ .\ (\text{no}+\text{pt}(u)g_{1f}).\ /\ (\text{pt}(u)\ g_{2f}(1+\epsilon)) \tag{30}$$

β1(β1>1)=0;
β2=1-β1;

2. Sum rate of fair power allocation

$$C1 = log2(1 + pt(u) * \beta 1.* gf./(pt(u) * a2.* gf + no)) \tag{31}$$

$$C2 = log2(1 + pt(u) * \beta 1.* gn./(pt(u) * a2.* gn + no \tag{32}$$

3. Cumulative SR calculation

$$C\_sum(u) = mean(C1 + C2) \tag{33}$$

End
End Algorithm

8. DISCUSSION AND SCALABILITY

The paper proposed to design the NOMA- Massive MIMO architecture using distance adaptive multi user power allocation and evaluated the effectiveness of tweaked initial estimate based ADMM-IND design. Proposed methodology offers energy efficient and fast convergence detector. Following major discussions are addressed after comprehensive simulations.

- It has been noted that the majority of detectors, such as GS, CG, and NAS, did not provide good BER performance; however, infinity norm detector ADMIM provides the lowest BER and exhibits substantial comparative efficiency. Tweaking the initial estimate with RCO may improve the BER performance of existing AMDIM detectors.
- It is noted that as size of M-MIMO channel increases the SNR performance decreases and it require higher SNR relatively to achieve optimal BER performance.
- The M-MIMO is evaluated employing Monte Carlo (MC) simulation, where 10000 iterations are used. This approach improves the ADMIM detector performance significantly and is capable of achieving optimal BER.
- Proposed approach adopts NOM user power allocation in ration of their distance. This approach is beneficial to improve optimal power utilization and saves network energy.
- As a limitation designing the integration of existing MIMO system with NOMA system is still an ill-posed problem. There is still significant chance of BER improvement.
- The performance may be improved for the rectangular channel state matrix such as 8×4 the case with NOMA with multi-used MIMO system.

9. CONCLUSION AND FUTURE WORKS

The aim of this study is to construct an effective IND for huge MIMO systems by utilizing the alternate directions mechanism for multipliers (ADMM) oriented convex optimization. The method's quick speed or pace of convergence is one of its main advantages. The purpose of the paper was to examine the error rates for various MIMO sizes and M-QAM constellation orders. An adaptive minimized constellation order (RCO) proposal is put out in response to an increase in massive MIMO channel size as well as user density. For seven MIMO detectors-matched filter (MF), MMSE, NAS, GS, CG, and suggested RCO-ADMIN detectors the effectiveness of box-based detectors is compared.

The proposed adaptive NOMA with M-MIMO system is evaluated using d vector for BER performance. The BER of the order of 7.6×10^{-7} is offered at the 4 dB lesser than the 64×64 antenna case using the proposed RCO with QPSK. But at the SNR range higher than 20dB mark it is proposed to employe the 16 QAM with a higher antenna dimension of 128 or 256dB SNRs. The Channel size is varied to 16×16, 32×32, 64×64, 128×128 and 256×256 for the capacity measurement experiment. It is concluded that increasing M-MIMO size may exponentially increase the channel capacity of the communication systems. For 16 times increase in size the capacity is improved 1.4 times approx.

The hybrid combination of the MMSE and the ADMIN-based iterative detector was employed in the suggested MD approach. Better BER performance could be achieved by the combination. The ADMIM loop count is set to 5, and the number of iterations is set to 10,000.

The best performance of MC situation is achieved at 128x128 MIMO as 3.1×10^{-7} BER at 22dB. It is concluded that as the MIMO size increases the SNR performance is decreases. It is concluded that proposed ADMIM-based detectors enhance SER by 3.1297, 2.7724, 2.7346, and 2.698 times compared to Neuman, CG, GS, and OCDBOX-based approximation and box-based MIMO detectors, respectively.

Overall it is concluded that using the proposed NOMA-M-MIMO system may increase capacity, sum rate, and BER performance considering the significantly higher traffic in future beyond 6G communication.

9.1 Practical implications and future works

Practical implications of NOMA power allocation for beyond 6G more flexible and efficient systems are:

- Traditional NOMA offers fixed systems while proposed adaptive NOMA modifies power allocation in real time according to user distance criteria. In addition to the distance factor considering the strong or weak channel based on strength improve the power allocation
- Practical implications of utilizing the RCO may offer simplified design of the MIMO receiver and also provide lower BER at lower SNR too. For BS with limited power the RCO is viable for reliable communication.
- The proposed ADMIM detector is particularly useful when there are actually fewer users compared to number of antennas on the receiving BS. Compared to traditional linear detectors, it performs better in these conditions.
- Practically proposed method offers tweaking the ADMM initial response. It may improve convergence speed and also reduced latency in system, Accurate initial estimate makes it possible to converge at optimal solution. This may also improve power efficiency of the MIMO detectors.
- Although choosing the single best for initial estimate is a difficult task. Choosing wrong initial estimate may slow down the convergence.

9.2 Future scopes

In the future there is significant scope of improvement in BER performance for NOMA-MIMO system. The optimization and deep learning methods can be used for better performance of the system. It is also possible to evaluate the performance of a larger number of NOMA users. It is suggested that simulation power and resource distribution be simulated in the future. There is room for improvement in the allocation of power while maintaining data privacy. In the future ADMM detector can also be combined with square detector or method of the lattice reduction to improve the performance especially for massive MIMO.

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