COMPRESSED SENSING-BASED RECEIVERS FOR SPATIAL MODULATION-MIMO NOMA SYSTEMS

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Abstract

Spatial modulation (SM) offers a promising solution to the demands of up-and-coming wireless networks. In this thesis, the Generalized Orthogonal Matching Pursuit (gOMP) algorithm is introduced into the receiver of NOMA aided SM-MIMO system to improve processing speed and reduce computational complexity. Furthermore, we present comprehensive analysis of the latest research contributions for NOMA based SM-MIMO system which has considerable attention recently. In addition, we focused our attention on the CS based receivers for NOMA based SM and compared the complexity which contributes performance degradation, with typical ML detectors. Detection of SM can be thought of as a process of sparse reconstruction, due to its an inherent property of sparsity. The sparse signal can be detected by Compressed sensing (CS) algorithm which became competitive alternatives. Some modified CS detection algorithms which showed improved performance compared to the conventional CS based once, have not been adopted in NOMA based SM-MIMO system. We formulate the recovery problem by exploiting the SM-MIMO communication system as downlink power domain NOMA where the base station supports more users in downlink scenario. Also, we deployed a low complexity pairing in this system to increase sum throughput. In addition, we analyzed the behavior of gOMP algorithm at this system. Simulations show that the gOMP detector outperforms conventional CS detection schemes.

Keywords:

Spatial Modulation (SM), Non-Orthogonal Multiple Access (NOMA), Compression Sensing (CS), Generalized Orthogonal Matching Pursuit (gOMP).

Declaration

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1 INTRODUCTION

1.1 Background

Spatial Modulation (SM) is an emerging technique which addresses the challenges of future wireless communication. Since the available spectrum is limited, spectral efficiency is the key challenge in the modern communication system. It is obvious that more data rate can be achieved by using Multi Input Multi Output (MIMO) technique. Unfortunately, it does not lead to Electric Efficiency (EE). Since, MIMO is associated with circuits, it leads power dispersion which depends on the number of transmit antennas as well as the receive antennas. Fortunately, the SM system requires only single Radio Frequency (RF) chain, whereas large scale MIMO systems require multiple RF chains. By addressing issues related to energy efficiency and spectral efficiency, SM has emerged as a promising solution for various challenges. It holds the potential to overcome numerous problems in the future. Thus, it will be well suited for next generation wireless communication.

In a single active antenna SM ($N_t \times N_r$) system the binary source is treated as a group of $\log_2(N_t) + \log_2(M)$ bits block where M denotes size of the signal constellation diagram as illustrated in Figure 1.1. The number of transmit and receive antennas are denoted by N_t and N_r respectively. SM mapper processes each block, breaking it down into two sub blocks. A sub block $\log_2(N_t)$ bits are used for antenna selection. During that instant, the relevant antenna is then activated, while the others remain inactive. The other sub block $\log_2(M)$ bits are mapped into a transmitted symbol. After this process, the signal vector is passed through over a MIMO channel.

In contrast, the symbol rate is limited in the SM system compared to conventional modulation since single transmit antenna is used at any time instant [1]. This leads to concern more in Generalized Spatial Modulation (GSM) that enables more active antennas at any instant, instead of only one in SM [12]. The Generalized Spatial Modulation system with N_P active antennas, allows to activate more than one antenna simultaneously to transmit the same modulated symbol. The number of active antenna combinations is $\binom{N_t}{N_P}$ which is greater than the single active antenna SM ($N_t \times N_r$) system. One can select $2^{\log_2 \binom{N_t}{N_P}}$ combinations among all $\binom{N_t}{N_P}$ combinations which can carry $\left\lfloor \log_2 \binom{N_t}{N_P} \right\rfloor$ information bits[1]. Achieving higher transmission rates is possible with GSM. However, the detection algorithm must be able to estimate both the index and the transmitted symbol, which is a crucial aspect of the system.

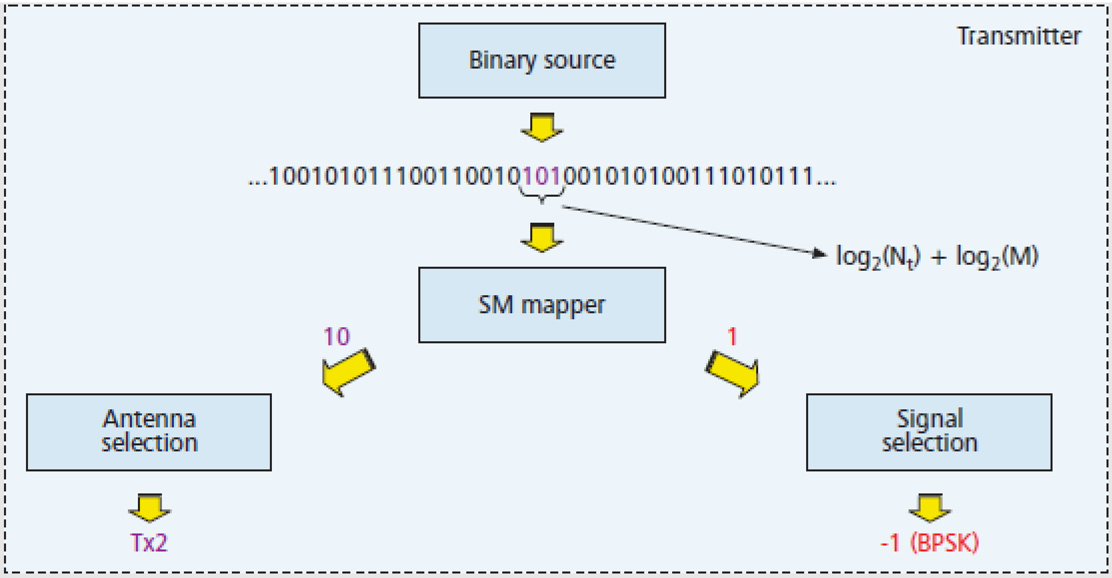

Figure 1.1: Illustration of SM-MIMO

Non-Orthogonal Multiple Access (NOMA) is a technique that can allocate non-orthogonal resources to multiple users, which makes it possible to accommodate a larger number of users compared to conventional orthogonal multiple access (OMA) systems [18]. NOMA aided SM is an emerging technique on these days since it overcomes the key challenges of multi user communication. The transmitter takes advantage of superposition coding, while the receiver strategically employs successive interference cancellation (SIC). This well-coordinated utilization of multi-user detection techniques effectively manages interference and optimizes the system's performance. In contrast, interference cancellation will become more complex while increasing the number of users. Moreover, error propagation degrades the system performance. It paved the way to researchers to obtain effective detection algorithms.

1.2 Detection Schemes for SM-MIMO Systems

In order to recover the signal, the receiver must detect both the active antenna index and the corresponding signal constellation symbol associated with that active transmit antenna. Accurate detection of these parameters is crucial for successful signal recovery. There are two types of detection techniques such as joint detection and separate detection. The joint detection algorithm simultaneously decodes both the active antenna index and the corresponding signal constellation symbol. The maximum likelihood (ML) detector belongs to the joint detection category, which involves simultaneous detection of both the active antenna index and the corresponding signal constellation symbol. This method is widely used due to its ability to provide accurate detection results. The ML detector aims to find the hypothesis that maximizes the likelihood of observing the received signal, given a set of possible transmitted signals and the statistical properties of the noise. Despite its high accuracy, the ML detector suffers from exponentially increasing computational complexity with an increase in the number of active antennas and the size of the signal constellation. This can pose significant challenges for practical implementation of the detector in real-world scenarios. When using the ML detector for detection in the M -ary GSM system, the computational complexity is approximately $O(M^{N_P})$ where, N_P represents the number of active antennas [6]. As such, the complexity of the ML detector increases exponentially with an increase in the number of active antennas N_P. The Separate or decoupled detection method acts based on two steps approach. First it determines the transmit antenna index. After that, it demodulates the signal constellation symbol which transmitted from that active antenna. The complexity is lower in the separate detection algorithm than the joint detection algorithm due to the reduced computation. However, the separate detection algorithm always suffers from performance degradation than the joint detection algorithm.

In order to design a receiver for SM that can perform optimally while maintaining low complexity, it is crucial to develop detection algorithms that can efficiently manage and process the received signals. These algorithms need to strike a balance between performance and complexity, thereby enabling practical implementation of SM systems. Compressed sensing (CS) is an innovative technology that enables the reconstruction of signals in under-determined systems, even the number of receive antennas to match or exceed the number of transmit antennas. This breakthrough technology has opened up new possibilities for signal processing and has the potential to significantly improve the performance of wireless communication systems. Even though the SM-MIMO systems consist a lot of antennas, only small number of antennas among them are enabled during each instant of transmission. Thus, most elements of signal vector are zero. Since the SM has an inherent property called sparsity, the detection can be considered as a sparse reconstruction problem. CS is the most suitable technique for the detection of sparse signals. Researchers are actively working on developing low complexity detection schemes based on CS that can deliver optimal performance. By leveraging the benefits of CS, these schemes aim to enhance the efficiency of signal processing while maintaining low computational complexity, thereby enabling practical implementation of CS-based detection in real-world scenarios.

1.3 State of art

Conventional detection schemes for SM can be broadly classified into two categories - linear detection schemes and ML detection. While linear detection schemes such as Minimum Mean-Squared Error (MMSE) detection and Zero-Forcing (ZF) detection are commonly used, they are known to have limited performance in terms of accuracy and efficiency. Moreover, ML detectors are restricted due to the high complexity since the scale is large. As such, there is a growing need for more advanced and effective detection schemes to improve the overall performance of SM systems. Fortunately, the detection of SM signal can be considered as a sparse reconstruction problem since the signal vector satisfies sparsity. The Sparse signal can be detected by CS algorithm which became competitive alternatives with low complexity. Towards this direction, researchers are engaged to develop CS based detectors for SM and GSM system.

To address the challenges posed by complexity in SM and GSM detection, researchers proposed the use of CS techniques. Specifically, algorithms such as Orthogonal Matching Pursuit (OMP), Basic Pursuit (BP), and Compressive Sampling Matching Pursuit (CoSaMP) showed promise in reducing the computational complexity of detection while maintaining high levels of accuracy. These CS-based detection algorithms were successfully implemented in SM-MIMO and SM-NOMA systems, thereby demonstrating their potential for improving the efficiency and effectiveness of wireless communication systems. The proposed OMP based detectors in [2] and [3] had low complexity for the large-scale SM systems. By formulating signal detection as a block sparse recovery problem, researchers achieved significant improvements in detection performance. In [7] and [8], to enhance the performance of the terrestrial return channel with NOMA and the uplink channel with NOMA, researchers structured signals as block-sparse vectors. The block-sparse approach showed promise in improving detection accuracy and efficiency, particularly in the context of multiuser signal detection. In particular, a block sparse CoSaMP algorithm was proposed for GSM-based detection in the NOMA systems. In addition, recent research demonstrated that certain algorithms were not traditionally used in NOMA systems can achieve high performance and low complexity compared to conventional CS algorithms. The approaches like the Extended OMP (eOMP) algorithm [9] and the generalized orthogonal matching pursuit (gOMP) algorithm [10] which showed to outperform conventional CS methods in certain scenarios. The promising results highlight the potential for new and innovative approaches to improve the performance of NOMA and other wireless communication systems.

1.4 Statement of the problem

SM-MIMO is a technique that overcomes the challenges such as energy efficiency and spectral efficiency. After introducing NOMA into SM-MIMO, NOMA aided SM-MIMO has emerged as an attractive technology in multi user communication that will fulfil the requirement of the future wireless system. On the other hand, the challenge of SM or GSM falls on the receiver end since the conventional SM detectors suffer from complexity and performance degradation. Linear detection schemes such as MMSE and Zero-Forcing detection have limited performance. Although ML detectors offer optimal performance, they can be limited by their high computational complexity, particularly when dealing with large-scale systems. However, sparse reconstruction methods offer a promising alternative for signal detection in SM systems, as the signal vector can be considered as sparse. The sparse signal can be detected by CS algorithm which became competitive alternatives with low complexity. Researchers are actively exploring the use of CS for signal detection in SM and GSM systems. By exploiting sparsity in the signal vector, CS-based detection algorithms can offer improved performance and lower complexity compared to traditional detection methods. As such, there is growing interest in developing CS-based detectors for these systems.

Recently, several well-known CS detection algorithms have been adapted for use in SM-MIMO and NOMA systems. The algorithms, such as OMP, BP, and CoSaMP, offer improved performance and lower complexity compared to traditional detection methods. BP algorithm has more convex relaxation than OMP. However, it is not recommended for detecting sparse signals, if the signals consist of noise [6]. The OMP algorithm has the execution speed is higher than compared with other algorithms [9]. However, when the OMP is applied to the detection of the SM-MIMO system, there may have some practical limitation due to the complexity which is quite involved with the size of matrix [10]. The CoSaMP algorithm has more running time compared to other CS algorithms. In [7], [8], a novel approach to detecting multi-user SM signals by formulating the problem as a block sparse recovery issue. To achieve this, a block sparse CoSaMP algorithm was developed.

However, the block sparse CoSaMP algorithm leads more complex to mitigate SIC at user end when the system becomes power domain downlink NOMA. Thus, the detector should be relaxed from drawbacks of conventional CS technique in order to adopt power domain NOMA. Even though, there are several CS algorithms proposed for the detection of sparse signal, so far, a few CS based detectors have been adopted in NOMA based SM system. The gOMP algorithm is a modified version of OMP algorithm which has not been adopted in NOMA aided SM-MIMO system. By using the gOMP algorithm a k-sparse signal can be reconstructed in k steps by selecting $S(>1)$ atoms in each iteration whereas the same signal can be reconstructed in k steps by selecting one atom in each iteration by using the OMP algorithm [10]. That is, S indices are identified per iteration in gOMP algorithm. It causes to have better processing speed and low computational complexity.

1.5 Objectives and scope

1.5.1 Objectives

1. Exploit the SM-MIMO communication system as downlink NOMA where the base station supports more users in downlink scenario and modeled the system as power domain NOMA.

2. Apply gOMP algorithm for the SM detection at the receiver end which has not been used in NOMA aided SM-MIMO system.

3. Analyze performance of gOMP algorithm by comparing successful recovery of signals.

4. Analyze the BER and compare the performance with other conventional CS algorithms using simulation.

1.5.2 Scope

Develop competitive alternative receiver by using low complexity gOMP algorithm, in order to reach high performance at the receiver of NOMA aided SM-MIMO system.

1.6 Methodology

- The proposed methodology involves utilizing the SM technique to modulate a multi-user signal in a downlink NOMA system. The system is designed to allow the base station to support a larger number of users in the downlink scenario, resulting in more efficient use of resources.
- Apply gOMP algorithms which is not used in the NOMA based SM system and reconstructs the sparse signal by selecting more than one index in each iteration in order to reach high performance at the receiver.
- Critically analyze the performance of gOMP algorithm by comparing BER as well as the percentage of successful recovery of signals with various CS based detection algorithms.
- Structure the SM system as downlink power domain NOMA system. And modeled that users in a base station are divided into groups which having only two users in each group.
- Modulate the multiuser signal through SM technique in the downlink NOMA system. Here modulated signal for each user within a group is shared same channel resource. The superposition coded NOMA signal transmitted from the base station by applying simple power allocation method.
- Apply the same algorithm to both the far user and the near user.
- Critically analyzed BER performance. Observe the BER variance of far user by applying direct demodulation. Also plot the variation of BER for near user through SIC at the user end and compare with various CS based detection algorithms.

1.7 Notation

The following notation is used. Scalars are shown in both lowercase and uppercase letters. Column vectors are shown in boldface lowercase letters and Matrices are shown in boldface uppercase. The ith entry of vector $\boldsymbol{x}$ is denoted by $\boldsymbol{x}_i$. The (i, j) th entry of matrix $\boldsymbol{X}$ is denoted by $\boldsymbol{X}_{i,j}$. Transpose, Hermitian, complex conjugate, and square absolute values are denoted by $(\,.\,)^T$, $(\,.\,)^H$, $(\,.\,)^*$, and $\lfloor\,.\,\rfloor^2$ respectively. $Re(\,.\,)$ and $Im(\,.\,)$ are real and imaginary parts of a complex valued number. $\lfloor\,.\,\rfloor$ denotes the floor operation. $\binom{\cdot}{\cdot}$ denotes binomial coefficient.

2 LITERATURE REVIEW

In this chapter, a comprehensive literature review on the existing work of CS-based detection schemes for SM-MIMO and SM-NOMA schemes is presented. The different NOMA-SM schemes presented in the literature are analyzed in the first part of this chapter. In the second part, CS based detection schemes proposed in the literature are discussed.

2.1 NOMA-SM Schemes

Since the telecommunication industry understood the importance of SM, researchers have put considerable effort on developing SM technologies. During the last decade, there is a large body of research exploring various SM technologies such as GSM [11], [12], Differential Spatial Modulation (DSM) [13], Quadrature Spatial Modulation (QSM) [14], Enhanced Spatial Modulation (ESM) [15], and so on. Through the development of SM schemes, offers a flexible framework that can adapt to varying needs and strike a balance among key factors such as spectral efficiency, energy efficiency, deployment cost, and overall system performance. Space-time block coding (STBC) was combined with SM in [16]. The STBC-SM scheme had significant improvement in BER performance compared to SM. Moreover, adaptive spatial modulation (ASM) was discussed in [17]. In ASM, the receiver in each time slot faces the crucial task of discerning the optimal modulation order that best suits the prevailing conditions and requirements. The major contributions of different SM schemes are summarized in Table 2.1.

Table 2.1:Summary of different SM schemes

Reference	Topic	Description
[20]	SM	Introduced the concept of SM and corresponding receiver performance was analysed
[21]	SM	Proposed a spectral efficiency multiple antenna transmission scheme named spatial modulation which maps multiple information bits into the physical location of single transmission antenna.
[22]	GSSK	The proposed modulation technique, known as GSSK, leverages fading in wireless communication by activating multiple TAs for data transmission.
[12]	GSM	Presented GSM which sending the same symbol from more than one TA at the time
[11]	GSM	The proposed GSM utilizes multiple active TAs to encode information bits and its performance was evaluated through simulation analysis. The BER performance of GSM was also compared with SM.
[13]	DSM	Introduced the idea of Differential Spatial Modulation (DSM)
[16]	SM	A new scheme called Space-time block coded Spatial Modulation (STBC-SM) was proposed, which combines both Space-time block coding and SM techniques.
[23]	SM	Discussed beneficial applications, challenges of SM. Described the world's first experimental activities of SM research field
[17]	SM	Discussed adaptive SM which has been adopted in most of the communication standard and also described detection techniques of SM.
[14]	QSM	A new MIMO technique called Quadrature Spatial Modulation (QSM) was proposed.
[15]	ESM	Introduced a SM technique called Enhanced Spatial Modulation (ESM) that transmits information bits from each active antenna by the constellations.
[24]	SM	Proposed the ordering algorithms of Sphere decoding for spatial modulation to reduce the computational complexity.
[25]	SM	Presented history of SM and future research Areas
[1]	SM	Presented latest results and progresses of SM research. Provided challenges and future directions of SM

NOMA techniques enable the utilization of the same resources, such as spreading code, time and frequency, for multiple access purposes [18]. Compared with conventional orthogonal multiple access (OMA), NOMA provides higher spectral efficiency by allowing non-orthogonal resource sharing and employing advanced interference management techniques [27], [29]. In the world of NOMA, there are two main categories of schemes: code domain and power domain. Code domain NOMA involves various strategies, including low-density spreading CDMA (LDS-CDMA), sparse code multiple access (SCMA), and multi-user shared access (MUSA). These techniques allow for multiple users to share the same resources without interference, providing increased efficiency and capacity in wireless communication systems [8]. Power domain NOMA is a technique where multiple signals from different users are combined using superposition coding at the transmitter. This method allows for efficient use of resources and increased capacity in wireless communication systems. However, in order to accurately detect and decode the individual signals at the receiver, SIC techniques must be employed. By performing SIC, the receiver can separate the multiplexed signals and decode them independently, improving overall system performance. Power allocation and user grouping play key roles in power domain NOMA schemes. The authors in [18] expressed the effects caused by different power allocation factors in NOMA. Different user grouping and the power allocation methods were presented in [19], [27] and [29] to improve the performance and data rate.

NOMA aided SM is an emerging technique in multiuser communications. The combination of NOMA and SM has paved the way to overcome the challenges in multiuser communications. High spectral efficiency, energy efficiency and interference mitigation can be achieved in the NOMA aided SM [1]. In general, the channel gain of each user is different which helps to mitigate the effects of intra-group interference in NOMA systems. In [18], performance degrading issue was addressed when the users have the same channel gain. To address this particular issue, a novel approach was introduced which involves a switching mechanism between NOMA and SM. Moreover GSM [19], QSM [27], Precoded Spatial Modulation (PSM) [26] and Block Spatial Modulation (BSM) [28] techniques were introduced to the NOMA in an effort to improve energy and spectral efficiency in wireless communication systems. The major contributions on NOMA based SM schemes are summarized in Table 2.2.

Table 2.2: Summary of NOMA-SM schemes

Reference	**NOMA Scheme**	**Description**
[18]	NOMA-SM	A novel approach was introduced which involves a switching mechanism between NOMA and SM. The authors expressed the effect of different power allocation factor in NOMA
[29]	NOMA-SM	Proposed NOMA SM to achieve high spectral efficiency with interference mitigation
[19]	NOMA-GSM	Proposed power allocation method and user grouping method for NOMA GSM systems to maximise the sum rate of users.
[26]	NOMA-PSM	Proposed a multi user MIMO transmission scheme called NOMA aided Precoded spatial modulation (NOMA-PSM) for overloaded downlink transmission.
[28]	BSM-NOMA	Proposed Block spatial modulation (BSM) based downlink NOMA which eliminates the requirement for SIC.
[27]	NOMA-QSM	Proposed a NOMA QSM system where spectral efficiency can be further improved.
[30]	NOMA-SM	Proposed grand free spatial modulation multi carrier NOMA for supporting large scale access of devices.

2.2 Detection Schemes for SM-MIMO Systems

In SM systems, it is necessary to detect both the active antenna index and the signal constellation symbol that is transmitted through the active transmit antenna. To accomplish this, researchers have developed various SM detection algorithms that can be broadly grouped into two categories: joint detection schemes and separate detection schemes. Joint detection algorithms can detect both the active transmit antenna index and the signal constellation symbol simultaneously, and a well-known example of this is the ML detector. The ML detector finds all possible transmit antennas and the transmitted symbol during the detecting process, to recover the information. However, the ML detector suffers from high computational complexity.

Specifically, the computational demands of the ML detector increase exponentially with the number of active antennas and the size of the constellation [6]. To address this issue, researchers proposed a hard-limiting based ML optimal detector [31], which offers lower computational complexity than the conventional ML detector while maintaining high detection accuracy.

In contrast, the separate(decoupled) detection method acts based on a two-step approach. In the first step, the index of active transmit antenna is determined by the detector. Next, the detection process involves identifying the signal constellation symbol that is being transmitted from the active transmit antenna. Consequently, the computational complexity associated with separate detection is lower when compared to the joint detection algorithm. However, while standalone detection techniques offer practical benefits, they may exhibit lower performance compared to joint detection. For this reason, it is critical to create detection methods that strike a balance between performance and complexity to ensure optimal results. On the other hand, SM consists a property called sparsity. Since there are only few non-zero entries in the transmitted signal vector, detection can be viewed as a problem of sparse reconstruction. Thus, it leads to research on sub optimal detection algorithm to detect sparse signal. Sparse signals can be detected by the CS-based algorithm which is considered as a revolutionized signal processing method. Recently, there has been increased in developing low complexity CS based detection methods with the aim of achieving satisfactory performance.

2.2.1 CS-based detection algorithms

This subsection focuses on reviewing the well-known CS based detection algorithms that are suitable for detecting sparse signals. The system model for SM-MIMO written,

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{w}, \tag{2.1}$$

where $\boldsymbol{y}$ represents the received signal vector, $\boldsymbol{H}$ represents the channel matrix, $\boldsymbol{w}$ denotes the additive white Gaussian noise (AWGN) and $\boldsymbol{x}$ denotes the modulated signal vector. The commonly discussed CS-based detection algorithms include BP [6], OMP [2] and CoSaMP [7], [8] are widely utilized for the detection of the sparse signal ($\boldsymbol{x}$). In addition, Approximate Message Passing (AMP) [34] and Sparse Bayesian learning (SBL) [35] algorithms gained significant attention recently. However, the performance loss is the major drawback of these typical CS detectors compared to joint detection. Researchers proposed modified versions of the above-mentioned conventional algorithms to overcome the performance issue yet maintain low deployment cost and reduce the computational complexity.

2.2.1.1 BP based detectors

Basic Pursuit formulates the problem as a l_1-norm minimization problem and tries to find the signal vector that minimizes the l_1-norm. The BP based detectors generally can recover the signal without the influence of the noise and the BP algorithm has more convex relaxation than the OMP [6]. However, the effect of the noise cannot be ignored in the practical application. Noticing this issue, a BP aided denoising (BPDN) detector which offers improved performance for noise variation over the other CS detectors, was proposed in [6]. The computational complexity of the BP algorithm is about $O((2N_t)^3)$ [3]. Hence, when applied to SM systems with a large number of antennas (N_t), BP detectors encounter significant computational complexity challenges.

2.2.1.2 Approximate Message Passing

In compressive sensing, AMP is used to recover sparse signals from a small number of linear measurements, making it particularly useful when dealing with large datasets. It is especially valuable in scenarios where the underlying signals are sparse or low-rank, and the number of measurements is much smaller than the signal dimension, making it suitable for dealing with large datasets efficiently. In [34], the generalized AMP (GAMP) was discussed and investigated in both noisy and noiseless scenarios.

2.2.1.3 Sparse Bayesian learning algorithm

Sparse Bayesian Learning is an algorithm used for variable selection and parameter estimation in statistical modeling. The primary goal is to identify and retain only the most relevant variables while effectively discarding irrelevant ones. SBL operates within the framework of Bayesian statistics, leveraging prior information and probability distributions to achieve its objectives. SBL distinguished by its unique advantages over other algorithms. In [35], authors analyzed SBL in a block sparse model where the simulations showed better performance. SBL stands tall as the perfect match for the specific requirements and bears the distinctive ability to gracefully address the challenge of variable selection.

2.2.1.4 CoSaMP based detectors

CoSaMP is an effective CS detection algorithm for the sparse signal. The CoSaMP algorithm solves a least-squares problem using the selected columns of channel matrix to obtain an updated estimate of the sparse signal. Some detectors based on CoSaMP algorithm were proposed recently, which applied for reconstructing sparse signals. Incorporating a block sparse model for sparse signal representation showed to result in enhanced performance by Block CoSaMP [7]. Additionally, a literature review [8] highlighted the development of an algorithm called Enhanced structured block-sparse comprehensive sampling matching pursuit (ESB-CoSaMP) which utilizes the CoSaMP approach for block sparse scenarios. The ESB-CoSaMP algorithm detected the transmitted signal of the active user in SM systems and showed lower BER compared with other CS detectors due to the block sparse structure. The main drawback of this type of detectors is that having high error performance for unbalanced antenna configuration [3].

2.2.1.5 OMP based detectors

OMP is an attractive CS based detection algorithm since the sparse signal can be estimated by using this algorithm. The OMP algorithm reconstructs the sparse signal by solving a least-squares problem using the selected atoms and their coefficients obtained from the projection step. Among the CS detection algorithms, the OMP stands out for its superior execution speed. However, there are certain issues faced during the practical implementation such as computational complexity, memory requirements, determining the convergence and stopping criteria. To address these issues and achieve enhanced performance, modifications were proposed to refine the OMP algorithm. The gOMP algorithm which is a modified version of the OMP algorithm was presented in [10]. The gOMP algorithm showed the improved recovery performance compared to the other conventional CS algorithms. Moreover, an OMP based scheme called extended OMP was proposed in [9]. The measurement requirements for extended OMP are comparable with that of BP.

As described in algorithm 1, OMP algorithm starts with an initial residual vector $\boldsymbol{r}$ equal to the measured signal $\boldsymbol{y}$ and an empty support set that keeps track of the indices of the selected atoms (columns) from the measurement matrix. In each iteration, the algorithm selects an atom that is most correlated with the current residual. This is done by calculating the inner product between each column of the measurement matrix and the residual vector. The atom with the highest correlation is added to the support set. Once an atom is selected, the algorithm projects the measurement vector onto the subspace spanned by the selected atoms in the support set. This projection operation computes the coefficients of the selected atoms that best approximate the measurements. After the projection step, the algorithm updates the residual vector by subtracting the projection from the original measurements. This residual represents the unexplained part of the signal. The algorithm iterates until a stopping criterion is met. This criterion can be a predetermined number of iterations or when the residual falls below a certain threshold. Finally, the OMP algorithm reconstructs the sparse signal through calculates the coefficient of the selected atom obtained from the projection step by solving a least-squares problem.

The OMP algorithm identifies the position of a non-zero element in each iteration. Thus, OMP recovers k-sparse signal in k iterations.

Algorithm 1 OMP For CS recovery [9]

Input:
Channel Matrix $\boldsymbol{H} \in \mathbb{C}^{N_r \times N_t}$
Received signal $\boldsymbol{y} \in \mathbb{C}^{N_r \times 1}$
Maximum iterations t_{max}

Output:
Estimated sparse signal $\bar{\mathbf{x}}$

Procedure:
1. Initialization:
    residual $\boldsymbol{r}^0 = \boldsymbol{y}$
    Index set $\Lambda^0 = \emptyset$
    Iteration counter $t = 0$
2. Increment $t = t + 1$
3. Choose the atom $\lambda^t = \underset{1 \leq j \leq N}{\operatorname{argmax}} \left| \langle \varphi_J, \boldsymbol{r}^{t-1} \rangle \right|$
4. Update $\Lambda^t = \Lambda^{t-1} \cup \{\lambda^t\}$
5. Update $\boldsymbol{x}^t = \boldsymbol{H}_{\Lambda^t}^{\dagger} \boldsymbol{y}$
6. Update $\boldsymbol{r}^t = \boldsymbol{y} - \boldsymbol{H}_{\Lambda^t} \boldsymbol{x}^t$
7. Do to step 2, if $t < t_{max}$; else terminate
8. Estimate $\bar{\mathbf{x}}$; i.e. $\bar{\mathbf{x}}_{\Lambda^t} = \boldsymbol{x}^t$

The gOMP algorithm is a modified version of the OMP algorithm [10]. By using the gOMP algorithm a k -sparse signal can be reconstructed in k steps by selecting S ($S > 1$) atoms in each iteration, whereas the same signal is reconstructed in k steps by selecting one atom in each iteration by using the OMP algorithm. In the gOMP algorithm, the identification of S indices is performed during each iteration. This leads to a better processing speed and lower computational complexity. The gOMP algorithm is presented in algorithm 2. A tabular representation of the pros and cons associated with CS based detection methods can be found in Table 2.3.

Algorithm 2 gOMP Algorithm for CS recovery [10]

Input:
Channel Matrix $\boldsymbol{H} \in \mathbb{C}^{N_r \times N_t}$
Received signal $\boldsymbol{y} \in \mathbb{C}^{N_r \times 1}$
Sparsity k
Number of indices for each selection S ($S \leq k$) $and\ S \leq \frac{N_r}{k}$

Output:
Estimated sparse signal $\bar{\mathbf{x}}$

Procedure:
1. Initialization:
   residual $\boldsymbol{r}^0 = \boldsymbol{y}$
   Index set $\Lambda^0 = \emptyset$
   Iteration counter $t = 0$
2. Increment $t = t + 1$
3. Choose the atom λ^t = set of indices corresponding to the S largest entries in $|\boldsymbol{H}^{t-1}\boldsymbol{r}^{t-1}|$. $(St_{max} \leq N_r)$
4. Update $\Lambda^t = \Lambda^{t-1} \cup \{\lambda^t\}$
5. Update $\boldsymbol{x}^t = arg\min_u \|\boldsymbol{y} - \boldsymbol{H}_{\Lambda^t}\, u\|_2$
6. Update $\boldsymbol{r}^t = \boldsymbol{y} - \boldsymbol{H}_{\Lambda^t}\, \boldsymbol{x}^t$
7. Do to step 2, if $t < t_{max}$ and $\|\mathbf{r}^{\mathrm{t}}\|_2 > 0$; else terminate
8. Estimate $\bar{\mathbf{x}}$; i.e. $\bar{\mathbf{x}}_{\Lambda^t} = \boldsymbol{x}^t$

Table 2.3: Summary of CS based detectors schemes

CS Algorithm	**Advantages**	**Disadvantages**
BP	• Low computational complexity:$O((2N_t)^3)$ • High convex relaxation.	• Not recommended for detecting sparse signals when the signals consist of the noise.
CoSaMP	• Offers demanding bounds on computational cost and storage	• High running time: $O(kWN)$. Has more running time compared to other CS algorithms.
OMP	• Low running time:$O(WN)$ • Low computational complexity: $O(kN_tN_r)$	• Practical implementation will become more complex with the size of channel matrix.
Extended OMP	• The measurement requirements are more similar to BP [9]	• Noise is not considered
gOMP	• No additional postprocessing operation[10] • Low running time	• Required the prior knowledge of index value S.
AMP	• The computational complexity is low $O(INk)$compared to some other iterative algorithms • Robustness to noise, and adaptability to various signal models	• Limited Adaptability to Changing Environments
BSL	• Identifying the most relevant variables and automatically discarding irrelevant ones.	• Computationally demanding when dealing with extremely large datasets or complex models

In the context of this scenario, N_t represents the count of transmit antennas, while N_r corresponds to the number of receive antennas. And k is the sparsity, W is the number of measurements, N is the signal length, I is the number of iterations

2.2.2 CS-based Detection Schemes for SM and NOMA-SM systems

In this subsection, CS based detection methods for both SM and NOMA-SM systems are reviewed. The researchers are carrying more attention on exploring the applicability of CS theory, including algorithms such as OMP, CoSaMP and BP, to the SM and the NOMA aided SM systems. For large-scale SM systems, the normalized CS (NCS) [2] and the extension of the normalized CS (E-NCS) [3] which are OMP-based detectors, possessed low computational complexity. Furthermore, the spatial modulation matching pursuit (SMMP) detector was proposed in [32] by using the CoSaMP algorithm. The SMMP detector was designed to detect SM signal from the multiple access channel. In [4], an enhanced bayesian compressive sensing (EBCS) detector was proposed for the GSM signal detection. The EBCS detector shows near-ML performance and the computational complexity is reduced up to 75% at high SNR compared with MMSE algorithm.

The complexity of the multiuser GSM signal detection in the NOMA system was discussed in [7]. The performance of signal detection can be enhanced when it is modeled as a block sparse recovery problem. Previous studies, such as [7] and [8], have utilized a block-sparse vector structure to improve the performance of signal transmission in the terrestrial return channel with NOMA and the uplink channel with NOMA, respectively. In the systems, ESB-CoSaMP detection algorithm based on block-sparse CoSaMP was proposed for multiuser signal detection. The combination of AMP based detection algorithm and expectation maximization (EM) was applied in uplink NOMA MIMO system [33]. The proposed joint detection showed fast convergence. In addition, block BSL algorithm was investigated in NOMA systems in order to solve block sparse reconstruction problem and compared the performance with BOMP algorithm [36].

Table 2.4 provides a comprehensive overview of the CS-based detection methods utilized for both SM and NOMA-SM. It is observed that certain proposed algorithms, which are yet to study for NOMA-SM systems, exhibit both superior performance and reduced complexity in comparison to conventional CS algorithms. For instance, the gOMP algorithm having excellent recovery performance compared to the OMP algorithm [10]. Additionally, the extended OMP algorithm proposed in [9] brings the number of measurements towards the BP. These advancements in algorithm design have opened up new possibilities for improving the efficiency and effectiveness of NOMA-SM systems.

Table 2.4- CS-based detection schemes for SM and NOMA-SM

Reference	**Description**	**Remark**
[2]	Normalized Compressed sensing detector was proposed GSM which is only required $O(N_p N_r N_t)$ complexity	The proposed CS detector is designed for separate detection and has been studied for SM-MIMO systems.
[9]	The extended OMP algorithm builds upon the original OMP algorithm and introduces additional improvements to enhance signal recovery from random measurements.	The proposed detection algorithm is designed for separate detection and yet to study for SM-NOMA systems
[10]	The gOMP algorithm extends the traditional OMP algorithm by incorporating a generalized pursuit strategy.	The proposed detection algorithm is designed for separate detection and yet to study for SM-NOMA systems.
[6]	Proposed a CS based detection algorithm termed as Basis Pursuit De-Noising (BPDN) for the GSM exploits the inherent sparse property.	The proposed CS detector is designed for joint detection and has been studied for SM/GSM systems.
[32]	A novel detection algorithm called "spatial modulation matching pursuit (SMMP)" was introduced, which incorporates CoSaMP to estimate the sparsity of transmitted signals in the multiple access channel. The algorithm benefits from its additional structure to enhance the accuracy of signal detection.	The proposed detection algorithm is designed for joint detection and has been studied for SM/GSM systems.

[4]	Proposed Enhanced Bayesian Compressive sensing (EBCS). Complexity is reduced up to 75% at high SNR compared with MMSE algorithm.	The proposed CS detector is designed for separate detection and has been studied for SM/GSM systems.
[5]	Proposed CS based multi user detector (MUD) which is used by both user and BS. The MUD aims to enhance the detection performance and mitigate interference in the uplink transmission.	The proposed CS detector is designed for joint detection and has been studied for large-scale SM-MIMO uplink scenarios.
[3]	To address the complexity issues associated with large-scale GSM systems, an OMP-based detector, referred to as the extension of the normalized CS (E-NCS), is proposed.	The proposed CS detector is designed for separate detection and has been studied for SM/GSM systems.
[7]	Proposed the ESB-CoSaMP detection algorithm based on block-sparse compressive sensing the NOMA system.	The proposed CS detector is designed for joint detection and has been studied for SM-NOMA systems.
[30]	Proposed 2 CS based detectors named as Joint Multiuser Matching Persuit (JMuMP) and Adaptive Multiuser Matching Persuit (AMuMP) which are suitable for Grant free SM NOMA system.	The proposed CS detectors are designed for joint detection and have been studied for SM-NOMA systems.
[33]	Proposed AMP based detection algorithm and expectation maximization (EM) termed as joint-EM-AMP.	The proposed CS detectors are designed for joint detection and have been studied for SM-NOMA systems.
[36]	Proposed a message passing based BSBL (MP-BSBL) algorithm for Grant free SM NOMA system.	The proposed CS detectors are designed for joint detection and have been studied for NOMA systems.

3 SYSTEM MODEL

In this chapter, the system model of NOMA aided MIMO-SM is presented as downlink NOMA. In the first part of this chapter, the transmission of power domain NOMA is briefly explained. The system is modeled to support more users in the downlink scenario, with the base station facilitating the process. Then the MIMO channel and Received signal are presented in following parts.

Table 3.1: Parameter Description

Parameter	Symbol
Number of transmit antennas	N_t
Number of receive antennas	N_r
Number of users	K
Number of active users	p
Size of the constellation	M
Received signal of user i	$\boldsymbol{y}_i$
Transmitted signal of user i	$\hat{\boldsymbol{x}}_{\boldsymbol{i}}$
symbol corresponded to the active antenna j of user i.	$\hat{x}_i(j)$
Channel matrix of user i	$\boldsymbol{H}_i$
Additive White Gaussian Noise of user i	$\boldsymbol{w}_i$
Transmit Power	P
Indices	S
Power allocation factor of user i	α_i
Multi-user SM modulated signal transmitted by all users	$\tilde{\boldsymbol{x}}$
Multi-user SM modulated signal transmitted by users in a group	$\hat{\boldsymbol{x}}$
Estimated signal at user 2	$\bar{\mathbf{x}}_{\mathbf{2}}$
The signal obtained after SIC at User 2	$\hat{\boldsymbol{x}}_2{}'$

3.1 Transmitter

In this scenario, a power domain NOMA system for the downlink is examined as in Figure 3.1. It is assumed that K users can be accommodated within this system. The number of antennas N_r is identical in each user. On the other hand, there are N_t transmit antennas at the base station. Moreover, a low complexity pairing scheme is deployed in this system to increase sum throughput [27]. It is assumed that users in a base station are divided into $K/2$ groups which having only two users in each group. SM modulated signal of user i denoted as $\widehat{\boldsymbol{x}}_i \in \mathbb{C}^{N_t \times 1}$, where $i \in \{1,2, \dots, K\}$.

$$\widehat{\boldsymbol{x}}_i = [\hat{x}_i(0), \dots, \hat{x}_i(j), \dots]^T \quad 3.1$$

Where, $\hat{x}_i(j)$, $j \in [1, N_t]$ denotes PSK/QAM symbol corresponded to the active antenna j of user i. Most elements of the signal vector are zero. Thus, the transmitted signal of each user is categorized as block sparse vector and it has same length N_t.

The rate of each user is $\log_2(N_t) + \log_2(M)$ bits per channel use (bpcu) [23]. It is considered that M-ary quadrature amplitude modulation (M -QAM) is used and the size of the constellation diagram is M. SM mapper divides every block into two smaller blocks during the processing stage. A sub block $\log_2(N_t)$ bits are used for antenna selection. During that instant, the corresponding antenna is enabled, while other antennas are remained inactive state. The other sub block $\log_2(M)$ bits are profiled into a transmitted symbol. Even during peak hours, this NOMA system operates with only a limited number of active users p ($p < K$) compared to the total number of supported users [7]. The system is designed to accommodate only a few users who are in the active state at any given time. If user i is not active, then transmitted signal of that user $\widehat{\boldsymbol{x}}_{\boldsymbol{i}}$ is expressed as zero vector.

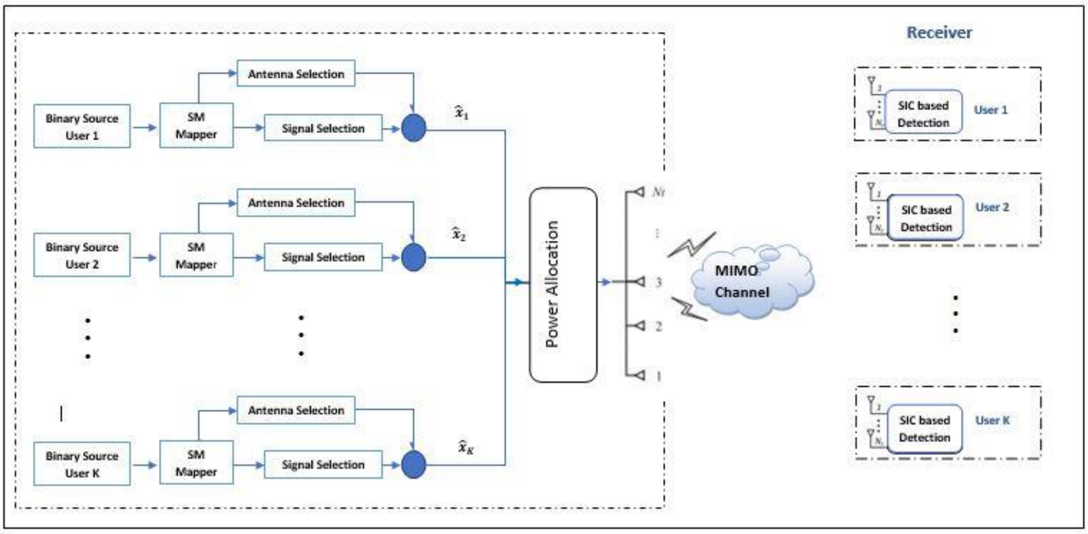

Figure 3.1: Power domain NOMA based Spatial Modulation

Let consider the CS based power domain NOMA system as shown in Figure 3.1, where all the transmit antennas have similar power amplifiers. Multiuser SM modulated signal transmitted by users $\widetilde{\boldsymbol{x}} \in \mathbb{C}^{N_t \times 1}$ is given by

$$\widetilde{\boldsymbol{x}} = \sqrt{P} \sum_{i=1}^{K} \sqrt{\alpha_i}\, \widehat{\boldsymbol{x}}_{\boldsymbol{i}} \qquad 3.2$$

where P is the transmit power and α_i represents the power allocation factor of user i. The total power of each group is identical. It is assumed that all the transmitters are equipped with equal number of antennas N_t. Let consider a group that has two distinct messages from user1 (far user) and user2 (near user). The corresponding SM modulated signals of user1 (far user) and user2 (near user) represent as $\widehat{\boldsymbol{x}}_1$and $\widehat{\boldsymbol{x}}_2$ respectively. The power allocation in this system is determined by two factors: α_1 and α_2, which correspond to the far user and near user, respectively. These factors are fixed according to the channel conditions in the power domain system. The far user is allocated a much higher power allocation factor compared to the near user. This allocation scheme is achieved through superposition coding at the transmitter side of the system. The superposition coded NOMA signal transmitted by each group is,

$$\widehat{\boldsymbol{x}} = \sqrt{P} \sum_{i=1}^{2} \sqrt{\alpha_i} \widehat{\boldsymbol{x}}_i \qquad 3.3$$

$$\widehat{\boldsymbol{x}} = \sqrt{P}\ (\sqrt{\alpha_1} \widehat{\boldsymbol{x}}_1 + \sqrt{\alpha_2}\, \widehat{\boldsymbol{x}}_2) \qquad 3.4$$

where $\widehat{\boldsymbol{x}} \in \mathbb{C}^{N_t \times 1}$, is the SM modulated transmitted signal which is a linear combination of $\widehat{\boldsymbol{x}}_{\mathbf{1}}$ and $\widehat{\boldsymbol{x}}_{\mathbf{2}}$.

3.2 MIMO Channel

After the process at the transmitter, the signal vector is passed through over a MIMO channel as illustrated in Figure 3.2. For the users in this SM MIMO-NOMA system, their respective channel coefficients are characterized by an uncorrelated Rayleigh fading channel model. This implies that the channels for each user are not correlated with each other, and the fading of each channel is described by a Rayleigh distribution. The channel Matrix of user $\boldsymbol{i}$ is expressed as $\boldsymbol{H}_i \in \mathbb{C}^{N_r \times N_t}$ where $i \in \{1,2, \dots, K\}$. The elements in this context are complex-valued random variables that are independent and identically distributed (i.i.d.). The channel gain of each user is different and it is assumed that $\|\boldsymbol{H}_K\|^2 > \cdots \|\boldsymbol{H}_2\|^2 > \|\boldsymbol{H}_1\|^2$, where $\|.\|^2$ donates the Euclidean norm. The recommended user pairing scheme is adopted to this system for reducing the complexity of SIC [27]. It is considered a group which has two users named as user1 and user2. The first user is far away from base station than the second user. Thus, the base station will allocate high power to user 1. Meanwhile, the SIC is implemented at the receiver side in NOMA-SM system to mitigate inter user interference.

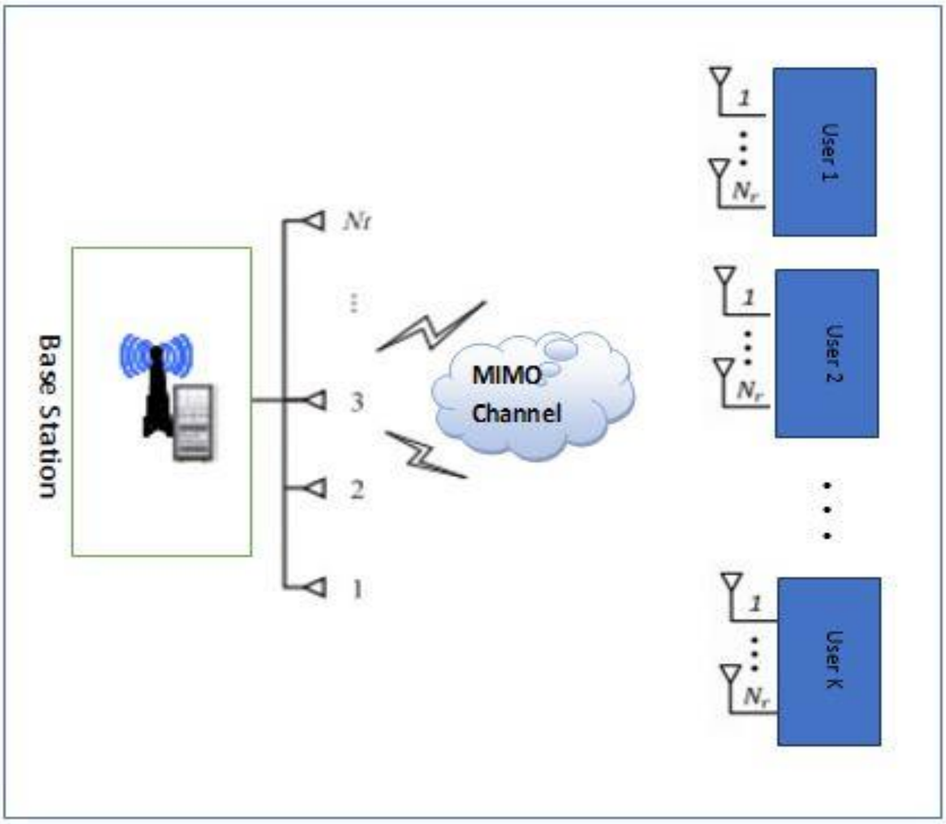

Figure 3.2: MIMO Channel

3.3 Received Signal

Due to the fact that only a small number of antennas are active at any given time, the signal vector in this system can be approximated as sparse. Consequently, the detection process can be viewed as a sparse reconstruction problem, which involves identifying the sparse vector from a set of measurements. The received signal can be written as,

$$\boldsymbol{y}_i = \boldsymbol{H}_i \widehat{\boldsymbol{x}} + \boldsymbol{w}_i \tag{3.5}$$

where, $\boldsymbol{y}_i \in \mathbb{C}^{N_r \times 1}$ refers to the signal that has been received by the user i and $\boldsymbol{H}_i \in \mathbb{C}^{N_r \times N_t}$ is the channel matrix of user i . $\boldsymbol{w}_i \in \mathbb{C}^{N_r \times 1} \sim \mathcal{CN}(0, \sigma^2)$ denotes AWGN of user i with variance σ^2. Here, $\widehat{\boldsymbol{x}}$ is the SM transmitted signal which is a linear combination of $\widehat{\boldsymbol{x}}_1$ and $\widehat{\boldsymbol{x}}_2$. SIC is a widely used technique in power domain NOMA systems, primarily implemented at the receiver. Its main principle involves granting priority to the user with the highest power allocation factor, enabling the direct detection of their signal using a conventional SM detector. Following the detection of the user with the highest power allocation factor using a conventional SM detector, the next step in SIC involves detecting the signal of the user with the next highest power. However, this requires the use of the SIC-based detector, which is designed to remove any interference caused by other users. This process repeats till the signals of all users are detected. Let consider the far user (user 1) processing at receiver. The received signal of user 1 can be described as $\boldsymbol{y}_1 = \boldsymbol{H}_1\hat{\boldsymbol{x}} + \boldsymbol{w}_1$, where $\boldsymbol{H_1}$ is Channel Matrix of user 1. This received signal can be rewritten as,

$$\boldsymbol{y}_1 = \boldsymbol{H_1}\sqrt{P}\,(\sqrt{\alpha_1}\hat{\boldsymbol{x}}_1 + \sqrt{\alpha_2}\,\hat{\boldsymbol{x}}_2) + \boldsymbol{w_1} \tag{3.6}$$

$$\boldsymbol{y}_1 = \boldsymbol{H}_1\sqrt{P}\,\sqrt{\alpha_1}\hat{\boldsymbol{x}}_1 + \boldsymbol{H_1}\sqrt{P}\sqrt{\alpha_2}\,\hat{\boldsymbol{x}}_2 + \boldsymbol{w}_1 \tag{3.7}$$

At user 1's end, the received signal is a combination of the modulated signal components of both users, with user 1 being allocated a significantly higher power allocation factor than user 2. Thus, the component $\boldsymbol{H}_1\sqrt{P}\sqrt{\alpha_2}\,\hat{\boldsymbol{x}}_2$ represents the interference. Due to the higher power allocation factor, the signal of user 1 can be obtained using a gOMP detector without the need for interference cancellation.

Now, let's focus on the received signal of user 2 (Near User) which can be described as $\boldsymbol{y}_2 = \boldsymbol{H}_2\hat{\boldsymbol{x}} + \boldsymbol{w}_2$, where $\boldsymbol{H}_2$ is Channel Matrix of user 2. This received signal can be rewritten as,

$$\boldsymbol{y}_2 = \boldsymbol{H}_2\sqrt{P}\,(\sqrt{\alpha_1}\hat{\boldsymbol{x}}_1 + \sqrt{\alpha_2}\,\hat{\boldsymbol{x}}_2) + \boldsymbol{w}_2 \tag{3.8}$$

$$\boldsymbol{y}_2 = \boldsymbol{H}_2\sqrt{P}\,\sqrt{\alpha_1}\hat{\boldsymbol{x}}_1 + \boldsymbol{H}_2\sqrt{P}\sqrt{\alpha_2}\,\hat{\boldsymbol{x}}_2 + \boldsymbol{w}_2 \tag{3.9}$$

The received signal at user 2 which is a linear combination of $\hat{\boldsymbol{x}}_{\boldsymbol{1}}$ and $\hat{\boldsymbol{x}}_{\boldsymbol{2}}$, consists a copy of the modulated signal of user 1. The processing of the received signal is illustrated in Figure 3.3.

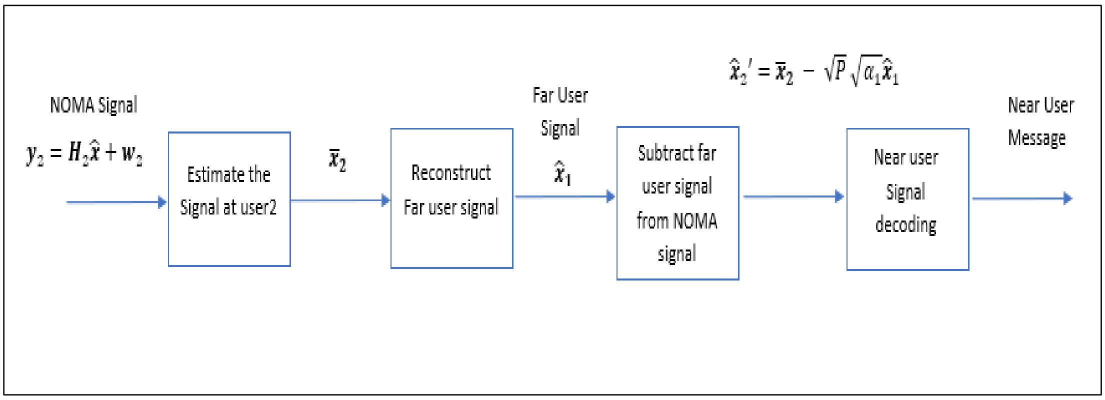

Figure 3.3: Near-User processing at Receiver

The signal at user 2 can be obtained by gOMP detector. Since $\alpha_2 < \alpha_1$, signal of User 1 (Far User) who has with high power can be decoded from the signal received at user 2. Then, the decoded signal is reconstructed and multiplied by the power allocation factor of user 1. After that, it is subtracted from the estimated signal at user 2. The signal of near user can be decoded from the signal obtained after SIC.

4 PROPOSED RECEIVER SCHEME

In this chapter, the recommended gOMP algorithm is described based on the system model presented in the previous section.

Table 4.1: Parameter description

Parameter	Symbol
Number of transmit antennas	N_t
Number of receive antennas	N_r
Multiuser SM modulated signal transmitted by users in a group	$\hat{\boldsymbol{x}}$
Received signal of user i	$\boldsymbol{y}_i$
Channel matrix of user i	$\boldsymbol{H}_i$
Additive White Gaussian Noise of user i	$\boldsymbol{w}_i$
Sparsity	k
Restricted Isometry Constant of order k	δ_k
Iteration	t
Residual at t^{th} iteration	$\boldsymbol{r}^t$
Index set at t^{th} iteration	Λ^t
Atom at t^{th} iteration	λ^t
Estimated signal at t^{th} iteration	$\boldsymbol{x}^t$
Estimated sparse signal at User i	$\bar{\boldsymbol{x}}_i$
Indices	S
Power allocation factors of User 1	α_1
Power allocation factors of User 2	α_2
Estimated signal at user 2	$\bar{\mathbf{x}}_{\mathbf{2}}$
The signal obtained after SIC at User 2	$\hat{\boldsymbol{x}}_2{}'$
The support set of estimated signal $\bar{\mathbf{x}}$.	$supp(\bar{\mathbf{x}})$

To determine the solution for a sparse signal in spatial modulated systems, optimization techniques involving l_1 norm and higher are employed [10]. However, it is crucial that the channel matrix $\boldsymbol{H_i}$ satisfies the "Restricted Isometry Property" (RIP) condition [9], which is defined as follows:

$$(1 - \delta_k)\|\widehat{\boldsymbol{x}}\|_2^2 \leq \|\boldsymbol{H_i}\widehat{\boldsymbol{x}}\|_2^2 \leq (1 + \delta_k)\|\widehat{\boldsymbol{x}}\|_2^2 \qquad 4.1$$

This condition must hold for all k -sparse signals $\widehat{\boldsymbol{x}}$, where δk is a constant ranging from 0 to 1. When an adequate number of antennas are available at the receiver, the RIP condition is typically satisfied in the channel matrix $\boldsymbol{H_i}$ with a high probability [7]. As the detection problem can be addressed through l_1-norm optimization, greedy algorithms [8] can be employed to solve the detection problem effectively. These algorithms aim to find the optimal solution by iteratively selecting the most significant features based on the l_1-norm optimization criterion.

The gOMP is a modified version of OMP algorithm. By using the gOMP algorithm a k-sparse signal can be reconstructed in k steps by selecting $S(> 1)$ atoms in each iteration whereas the same signal can be reconstructed in k steps by selecting one atom in each iteration by using the OMP algorithm [10]. That is, S indices are identified per iteration in the gOMP algorithm. It causes to have better processing speed and low computational complexity. There are three main steps in overall algorithm as described in Algorithm 2 [10].

Step 1: Initialize the iterative variable t, residual $\boldsymbol{r}^0$ and Index set Λ^t. At the beginning of the algorithm, it initializes the variables as $t = 0$ and $\boldsymbol{r}^0 = \boldsymbol{y}_i$ respectively. The Index set Λ^0 is initialized as Ø. Unlike the other conventional CS algorithms, the number of indices S is introduced for each selection which is satisfied $S(S \leq k)$ and $S \leq \frac{N_r}{k}$.

Step 2: Iterate to calculate Λ^t, $\boldsymbol{x}^t$ and $\boldsymbol{r}^t$ until the condition is satisfied. A simple variable t_{max} is used for controlling the iteration. This stopping criterion can be modified as per the requirement of the SM-MIMO system. At iteration t, the gOMP chooses the atom λ^t by finding the best matching index from the residual. The chosen atom λ^t is equal to the set of indices corresponding to the S largest entries in

$|\boldsymbol{H}^{t-1}\boldsymbol{r}^{t-1}|$. $(St_{max} \leq N_r)$. Then the gOMP updates the selected index set $\wedge^t = \wedge^{t-1} \cup \{\lambda^t\}$. After that, the gOMP obtains the best approximation of residual at t^{th} iteration $\boldsymbol{r}^t$ by a least square minimization method. Thus, the gOMP estimates k-sparse signal in k iterations by selecting $S(> 1)$ atoms in each iteration.

Step 3: Check if a stopping criterion is met. This can be a predefined number of iterations, a desired level of residual energy, or a certain threshold. Once the stopping criterion is satisfied, use the selected atoms and their corresponding coefficients to reconstruct the sparse signal $\bar{\mathbf{x}}$; that is $\bar{\mathbf{x}}_{\wedge^t} = \boldsymbol{x}^t$.

Through the gOMP detection, it is estimated both the active antenna index and the signal constellation. Let consider the receiver of the power domain NOMA system which having only two users in each group as mentioned in Chapter 3.1. In the power domain NOMA system, SIC is employed at the receiver, where the user with the highest power allocation factor is given priority. Initially, the SM detector directly detects the signal of this user. The SIC-based detector is then utilized to detect the signal of the user with the next highest power allocation factor, while eliminating the interference from other users. The received signal of far user can be described as,

$$\boldsymbol{y}_1 = \boldsymbol{H}_1\widehat{\boldsymbol{x}} + \boldsymbol{w}_1 \tag{4.2}$$

where $\boldsymbol{H}_1$ is Channel Matrix of user 1. The multi-user SM modulated signal $\widehat{\boldsymbol{x}} \in \mathbb{C}^{N_t \times 1}$ consists both of $\widehat{\boldsymbol{x}}_{\mathbf{1}}$ and $\widehat{\boldsymbol{x}}_{\mathbf{2}}$ components. Since the far user has weighted more than near user $\alpha_2 < \alpha_1$, the $\widehat{\boldsymbol{x}}_2$ component can be treated as an interference. Thus, the gOMP detector provides an estimated signal for user 1 ($\bar{\mathbf{x}}_{\mathbf{1}}$) that can be decoded without requiring interference cancellation.

Let consider the received signal of user 2 (Near User) which can be given as,

$$\boldsymbol{y}_2 = \boldsymbol{H}_2\widehat{\boldsymbol{x}} + \boldsymbol{w}_2 \tag{4.3}$$

where $\boldsymbol{H}_2$ is Channel Matrix of user 2. The signal detected by the gOMP algorithm at user 2 is denoted as $\bar{\boldsymbol{x}}_2$. This signal contains a linear combination of far user signal $\widehat{\boldsymbol{x}}_{\boldsymbol{i}}$ and near user signal $\widehat{\boldsymbol{x}}_2$. Since $\alpha_2 < \alpha_1$, signal of user 1 (Far User) who has with high power can be decoded from the received signal at user 2. Then, the decoded signal is reconstructed and multiplied by the power allocation factor of user 1. After that, it is subtracted from the estimated signal at user 2. The signal obtained after SIC is defined as,

$$\widehat{\boldsymbol{x}}_2{}' = \overline{\boldsymbol{x}}_2 - \sqrt{P}\sqrt{\alpha_1}\widehat{\boldsymbol{x}}_1 \qquad 4.4$$

which is equal to $\sqrt{P}\sqrt{\alpha_2}\widehat{\boldsymbol{x}}_2$. The signal of near user can be decoded by direct demodulation of remaining signal $\widehat{\boldsymbol{x}}_2{}'$.

The complexity of this detection algorithm can be derived as $O(kN_tN_r)$. In practical scenarios, the iteration number of gOMP can be significantly reduced since the number of indices S is introduced during each iteration. Because of this feature, the gOMP algorithm identifies multiple indices without any additional post processing operation. Thus, the proposed gOMP algorithm enjoys the benefits of this feature and processes in less running time. Thus, it causes to have better processing speed and low computational complexity. The gOMP detection scheme has several advantages, including its efficiency in sparse signal recovery, adaptability, and applicability in NOMA systems. Compared to some other sparse recovery algorithms, gOMP has relatively low computational complexity. It strikes a balance between performance and complexity, making it practical for real-time applications and systems with limited computational resources. However, it also comes with some limitations, such as sensitivity to noise, performance dependency on sparsity, and inherent iterative nature.

In SM NOMA systems, multiple users share the same time-frequency resources with different power levels and spatial positions. The gOMP detector can be used to detect the active users and recover their transmitted signals efficiently. Since SM involves transmitting information through the antenna index, the gOMP algorithm can help identify the active antennas and the corresponding transmitted symbols of different users. The application of the gOMP detector in SM NOMA systems can lead to improved user detection and signal recovery, better interference management, and optimized resource allocation. As with any signal processing algorithm, its effectiveness depends on the specific system setup and channel conditions, but gOMP's ability to exploit sparsity makes it a valuable tool in SM NOMA communication scenarios.

5 RESULTS AND DISCUSSION

In this section, the simulation results of gOMP detection are presented and compared with OMP, BOMP and CoSaMP detection schemes. The same detection scheme is applied at the receiver of SM-MIMO communication system of as well as power domain NOMA-SM systems. The system assumes that the user has N_t transmit antennas and the base station has N_r receive antennas.

5.1 Receiver of SM-MIMO Systems

This section focuses on presenting and comparing the simulation results of the gOMP detection scheme with other prominent detection schemes, namely OMP, Block OMP (BOMP), and CoSaMP. The evaluation primarily revolves around analyzing the Bit Error Rate (BER) performance of the gOMP algorithm in the context of a SM-MIMO system. The BER calculations are carried out by considering factors such as the active antenna index and the selection of the signal constellation. The receiver setup involves a total of $N_r = 22$ antennas, while the system comprises $p = 2$ active users with $N_t = 16$ antennas, responsible for transmitting the modulated signals. In this particular scenario, 4 QAM modulation is employed.

Table 5.1: Simulation Parameters

Parameter	**Values**
Number of transmit antennas (N_t)	16
Number of receive antennas (N_r)	22
Number of users (K)	4
Number of active users (p)	2
Modulation	4 QAM

The analysis of BER performance reveals that the gOMP algorithm exhibits similar performance characteristics to the CoSaMP algorithm. Figure 5.1 showcases the results, clearly indicating that the gOMP algorithm outperforms the other conventional CS detectors in terms of BER, particularly in low SNR scenarios. These findings underscore the effectiveness of the gOMP algorithm in mitigating errors and improving the reliability of signal detection, especially under challenging conditions characterized by weak or noisy signals. The superior BER performance of gOMP in low SNR situations positions it as a promising solution for enhancing the robustness and accuracy of CS-based detection algorithms.

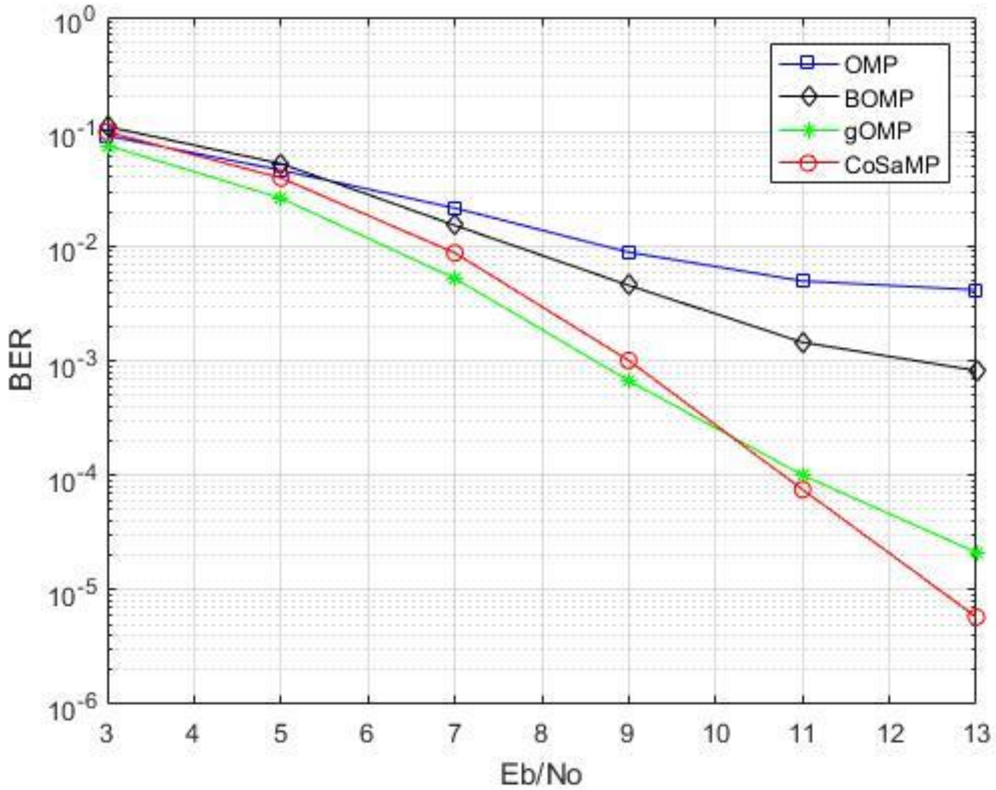

Figure 5.1: BER performance in SM-MIMO system

Additionally, we compare the performance of the gOMP detection scheme with other CS detectors. The evaluation is based on the successful recovery of a received signal in 64 different trials, measured by the probability of success. A recovery is considered successful if the distance between the modulated signal $\boldsymbol{x}$ and the recovered signal $\overline{\boldsymbol{x}}$ is insignificant [9], specifically $\|\overline{\boldsymbol{x}} - \boldsymbol{x}\|_2 \leq 10^{-6}$. In each trial, the SM technique is utilized to produce the modulated signal vector $\boldsymbol{x}$**.** The recovered signal vector $\overline{\boldsymbol{x}}$ is obtained using one of the following algorithms such as OMP, BOMP, CoSaMP, or the gOMP algorithm. In this system configuration, there are

$p = 8$ active users with $N_t = 8$ transmit antennas, and a 4 QAM scheme is applied for modulation.

Figure 5.2 provides a graphical representation showcasing how the percentage of recovered signals varies with the number of measurements. The results demonstrate that the gOMP algorithm performs similarly to the CoSaMP algorithm in terms of signal recovery. By examining the graph, it becomes evident that an increase in the number of measurements leads to a comparable trend in signal recovery for both the gOMP and CoSaMP algorithms. The percentage of successfully recovered signals remains relatively stable and comparable between the two algorithms.

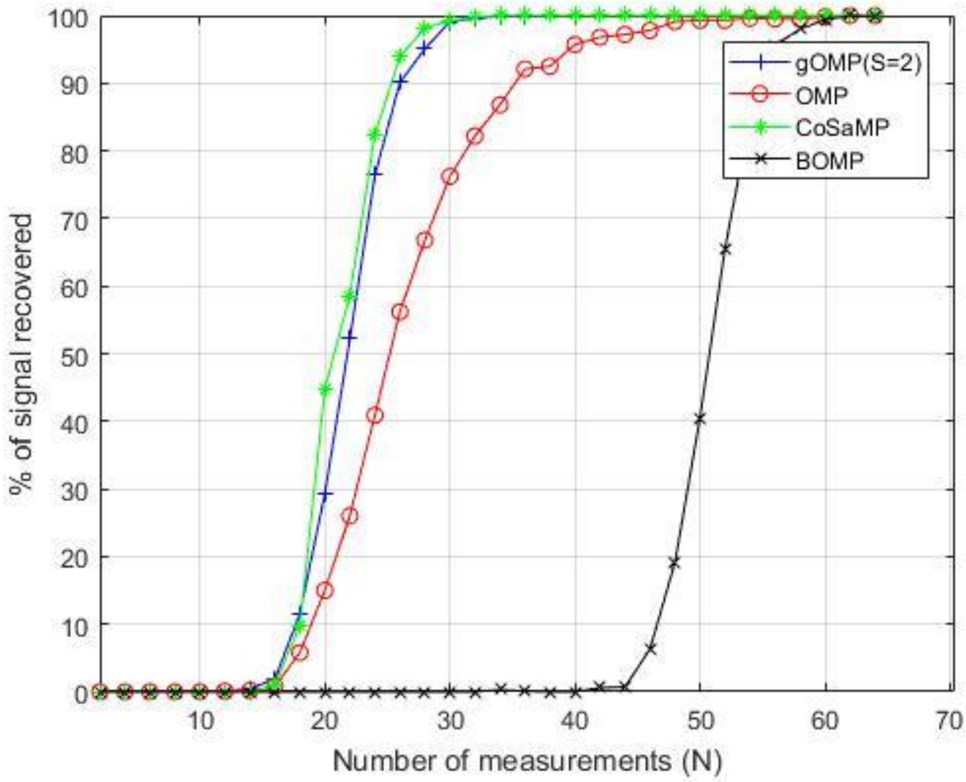

Figure 5.2: Performance Comparison

Furthermore, an interesting observation is that the signal recovery process becomes faster as the number of indices increases in the gOMP algorithm. This behavior is demonstrated in Figure 5.3, where the performance of the gOMP algorithm is showcased for different index values. Comparing the results, we can see that the gOMP algorithm with S=4 indices exhibits a performance closer to that of the CoSaMP algorithm, whereas the gOMP algorithm with $S = 2$ indices performs slightly differently. Even though CoSaMP recovered fast, it can lead to a relatively high computational cost, especially for large-scale problems or high-dimensional data. The gOMP algorithm with $S = 4$ identifies four indices per iteration, leading to improved processing speed compared to the gOMP algorithm with $S = 2$ indices or other OMP algorithms. This finding suggests that increasing the number of indices in the gOMP algorithm can contribute to faster signal recovery, making it a favorable choice for applications where speed is a crucial factor.

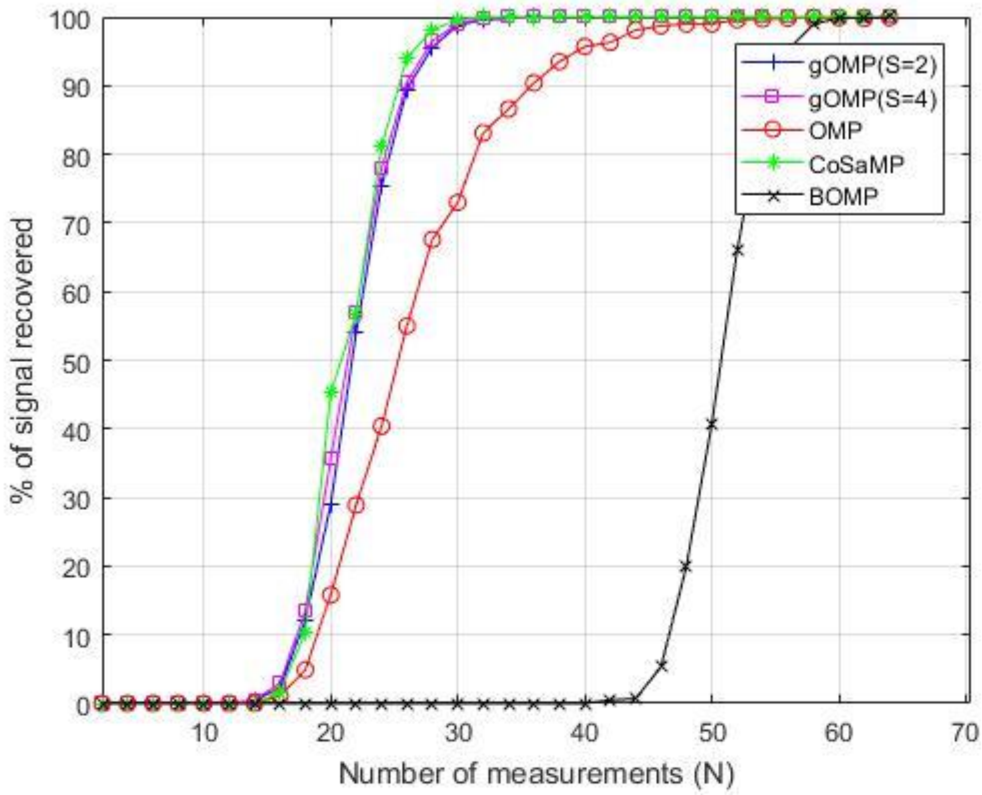

Figure 5.3: Comparison of the signal recovering performance of the gOMP algorithm with different index values

5.2 Receiver of power domain NOMA-SM Systems

In this subsection, the performance of the proposed CS based receiver in the power domain NOMA-SM system with 2 users is investigated. User 1 is considered as the far user whereas User 2 is the near user and they are equipped with $N_t = 4$ number of antennas. The superposition coded NOMA signals are transmitted from each user. It is assumed that when a user is closer to the transmitter, the modulated signal is weighted by power allocation factor α_2 (0.25). Similarly, when a user is far away, the modulated signal is weighted by power allocation factor α_1 (0.75). Thus, user 1 can be decoded directly since it is weighted with high power. To detect the signal for user 2, a SIC-based detector is employed, which removes interference from other users. Like in the previous scenario, the detected signals are obtained through OMP, BOMP, CoSaMP and gOMP ($S = 2$) algorithms.

Table 5.2: Simulation Parameters

Parameter	Values
Number of transmit antennas (N_t)	4
Number of receive antennas (N_r)	12
Number of active users (p)	2
Modulation	4 QAM
Indices (S)	2
Power allocation factors of User 1 (α_1)	0.75
Power allocation factors of User 2 (α_2)	0.25

The simulation results in Figure 5.4 demonstrate the BER performance of the proposed CS-based receiver for the far user in the power domain NOMA-SM system. Notably, the gOMP algorithm exhibits superior BER performance when compared to other conventional CS detectors, primarily due to its fast-processing speed. The BER estimation for the system was performed using the “berconfint” function in MATLAB, resulting in 90% confidence intervals for two algorithms: CoSaMP and gOMP. For the CoSaMP algorithm, the computed BER is 8.8615e-05. The corresponding 90% confidence interval suggests that the true BER for the system lies between 6.996e-05 and 1.072e-04. Conversely, for the gOMP algorithm, the computed BER is 2.823e-05. The associated 90% confidence interval indicates that the true BER for the system falls between 1.075e-05 and 4.570e-05. In summary, both algorithms have estimated BER values, along with their respective 90% confidence intervals and the gOMP algorithm showed lower BER range than CoSaMP algorithm.

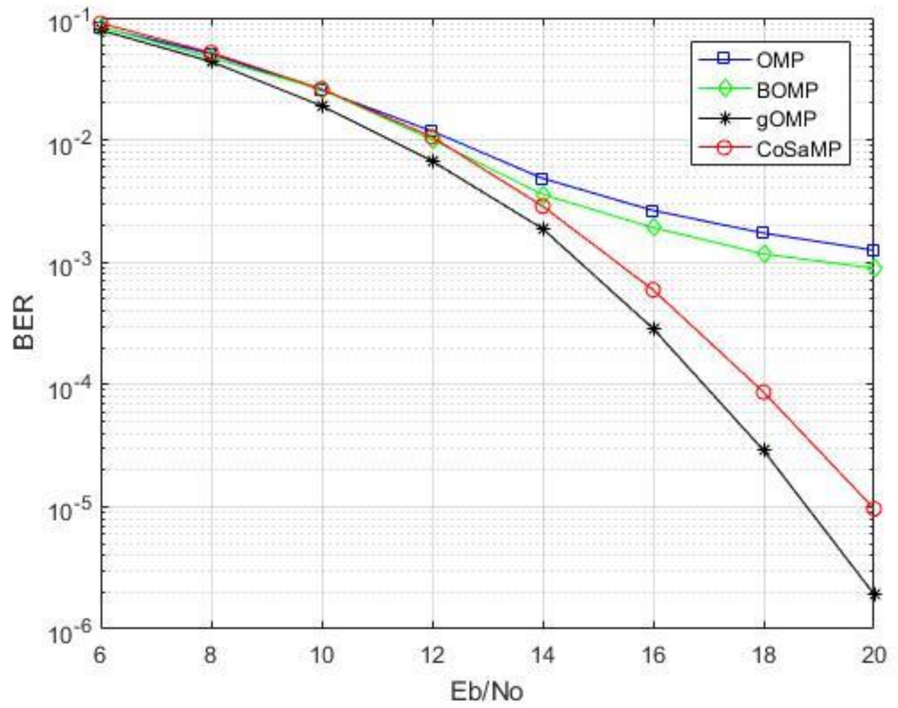

Figure 5.4: BER performance in NOMA-SM system for User 1 (Far User)

Moreover, we can observe the error floor in the OMP and the BOMP algorithms at high SNR. Figure 5.5 illustrates the simulation outcomes that demonstrate how the proposed CS-based receiver performs in terms of BER for the near user in a NOMA-SM system that utilizes power domain techniques. The near user signal is obtained by SIC based detectors. It can be observed that the proposed gOMP algorithm shows better BER performance compared to the other conventional CS detectors due to the fast processing speed. For the CoSaMP algorithm, the computed BER was 9.060e-05. The 90% confidence interval suggests that the true BER for the system lies between 7.532e-05 and 1.156e-04. Similarly, for the gOMP algorithm, the computed BER was 5.2000e-05 and the 90% confidence interval indicates that the true BER for the system is between 3.814e-05 and 7.048e-05. In summary, the BER estimates for both algorithms are provided along with their respective 90% confidence intervals and the gOMP algorithm showed lower BER range than CoSaMP algorithm. The confidence interval of both near and far users are summarized in Table 2.1

Table 5.3: Summary of confidence interval

User	Far User		Near User	
CS algorithm	CoSaMP	gOMP	CoSaMP	gOMP
Confidence level (%)	90	90	90	90
Calculated Eb/N0	18	18	18	18
Computed BER	8.8615e-05	2.823e-05	9.060e-05	5.2000e-05
Confidence interval (BER)	6.996e-05 to 1.072e-04	1.075e-05 to 4.570e-05	7.532e-05 to 1.156e-04	3.814e-05 to 7.048e-05

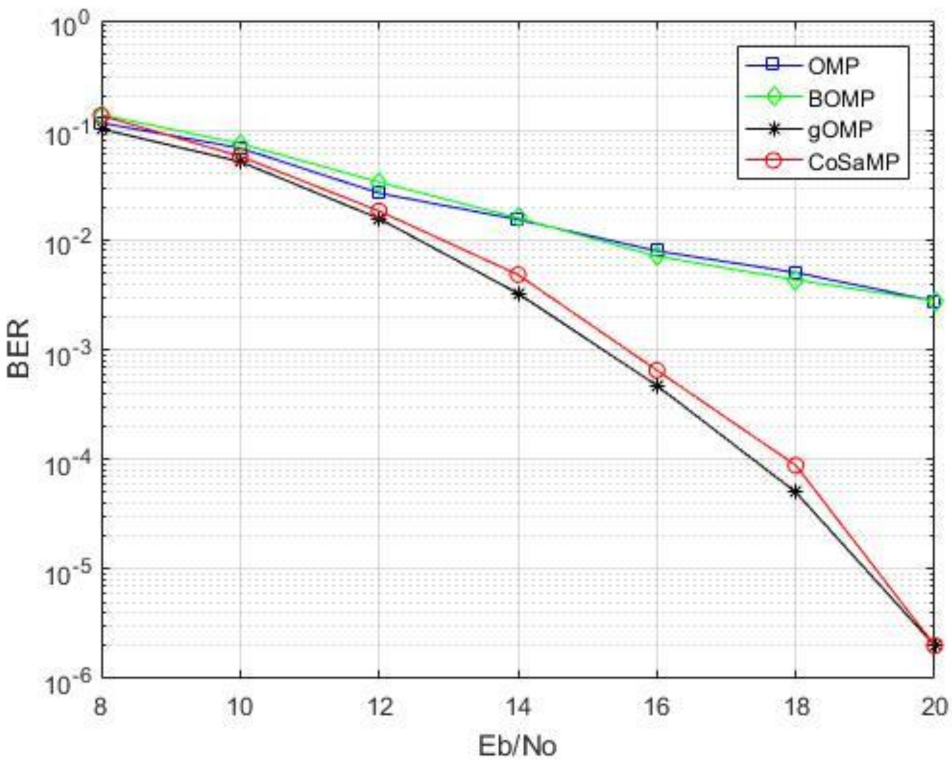

Figure 5.5: BER performance in NOMA-SM system for User 2 (Near User)

Moreover, the BER performance of the gOMP algorithm in the power domain NOMA-SM is further analyzed for different power allocation factors. The BER performance is investigated for near user and the near user signal is detected by SIC based gOMP detector. From Figure 5.6, we can observe that the user group which has 0.25 and 0.75 power allocation factors, shows optimal performance.

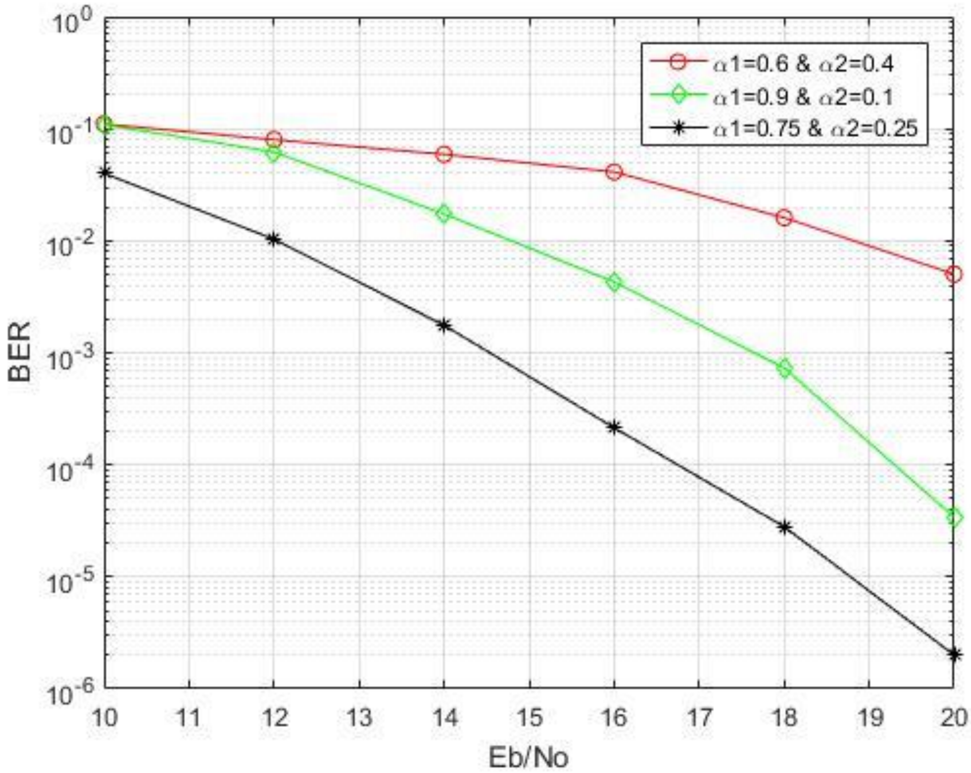

Figure 5.6: BER performance of the gOMP detector

6 CONCLUSION

In this thesis, a variety of recent advancements in the area of SM were explored and discussed on detection algorithms for the NOMA-SM system. We highlighted the advantages of CS based detection, which is more appropriate for SM system as it has a unique property called "Sparsity". Despite the fact that CS based detection algorithms have good performance, they still have high complexity, which is an open task in this area. Therefore, more research is being done to develop low complexity CS based detection schemes in order to get reasonable performance. It is observed that some modified CS detection algorithms having better performance compared to conventional CS based once, have not been adopted in NOMA based SM-MIMO system. The gOMP algorithm is a modified version of OMP algorithm which are yet to study for NOMA aided SM-MIMO system. We introduced the gOMP algorithm into the receiver of NOMA aided SM-MIMO system to improve processing speed and low computational complexity. We applied this algorithm on both SM-MIMO system and Power domain NOMA-SM systems. SIC is typically applied at the user end of the power domain NOMA communication systems.

The gOMP algorithm detects sparse signals by selecting more than one atom in each iteration, which results in better processing speed and low computational complexity. The simulation revealed that the gOMP detection scheme demonstrates superior performance compared to regular CS detection schemes. The gOMP algorithm is seen to be comparable to CoSaMP, and it improves significantly as the number of indices increased. Additionally, we found that the gOMP algorithm shows superior BER performance for both nearby and distant users in a power domain NOMA-SM system.

7 SUGGESTED FUTURE RESEARCH

The main achievement of our research is the integration of the gOMP algorithm into the receiver of a NOMA-assisted SM-MIMO system, resulting in enhanced processing speed and reduced computational complexity. Additionally, we have implemented a straightforward pairing scheme in this system, leaving room for exploring the receiver by applying alternative power allocation methods and user grouping techniques proposed in the literature for NOMA GSM systems. These paths hold potential for maximizing the overall sum rate of users. Furthermore, future investigations should focus on the applicability of the proposed detection scheme to various SM schemes by selecting activation patterns at the transmitter to address any shortcomings and devise suitable solutions.

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