Increases the overloading capability of NOMA with Sequence Block Compressed Sensing Multiuser Detection in 5G Communication

by

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A thesis submitted to the faculty of Electrical Engineering Department Military College of Signals, National University of Sciences and Technology, Rawalpindi as part of the requirements for the degree of MS in Electrical Engineering

Jul 2022

Abstract

To enable massive connectivity for the massive machine type communication (mMTC) in 5G communication non-orthogonal multiple access (NOMA) with sequence block-based compressed sensing multiuser detection (SB-CSMUD) is becoming a promising candidate. This process is done by exploiting the sporadic node activity of the MTC. The activity detection is enhanced in sequence block-based compressed sensing multiuser detection by instead of using a single sequence as a signature whole block of multiple spreading sequences serves as the signature of the node. The sequence block-based compressed sensing multiuser detection scheme besides increasing the spectrum efficiency improves the detection error rate as well. This thesis addresses the most prominent advancements in sequence block compressed sensing-based multi-user detection (SB-CSMUD) by increasing the overloading capability without increasing the number of available resources. By keeping resources constant, this thesis increases the overloading capability up to 100%.

Copyright

Declaration

I certify that the work *"Increasing the overloading capability of NOMA with Sequence Block Compressed Sensing Multiuser Detection in 5G Communication"* exhibited in this thesis has not been submitted in support of any other award or educational qualification either at this institution or elsewhere.

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Ammar Bin Abid

00000274857/MSEE24

Acknowledgements

I am grateful to Allah Almighty who has bestowed me the strength and the passion to accomplish this thesis and I am thankful to Him for His mercy and benevolence, without whose consent I could not have indulged myself in this work.

I would especially like to thank my supervisor Dr Mehmood Alam, Assistant Professor, Military College of Signals (NUST), for the amazing support he has provided me throughout my thesis. I am very grateful for the teachings of faculty members of Electrical Engineering Department Especially Dr Abdul Wakeel and Dr Shibli Nisar for their everlasting encouragement that has fueled my sense of continued determination over the years. I would also like to thank Dr Alina Mirza, Electrical Engineering Department, Military College of Signals (NUST) for her support during my research work.

I would like to show gratitude to my parents and siblings for all their care, love, and support through my times of stress and excitement.

Lastly, I express my gratitude towards SDO PTCL Mr. Babar Hayat without his motivation and continuous support, I would have not completed my master's degree on a high note.

Dedication

I dedicate my work to,

my parents who always encouraged my higher education, with their prayers, love and motivation and sacrifices all along.

my supervisors and friends for their support and patience during all the phases of my MS.

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List of Acronyms

Fifth Generation	5G
Global System for Mobile-Communication	GSM
Extreme Mobile Broadband	eMBB
Ultra-Reliable Low Latency Communication	URLLC
Massive Machine Type Communication	mMTC
Human Type Communication	HTC
Long Term Evolution	LTE
Non-Orthogonal Multiple Access	NOMA
Orthogonal Multiple Access	OMA
Compress Sensing Multi-User Detection	CSMUD
Power domain Non-Orthogonal Multiple Access	PD-NOMA
Base station	BS
Successive Interference Cancellation	SIC
Signal-to-Noise Ratio	SNR
Code domain Non-Orthogonal Multiple Access	CD-NOMA
Message passing algorithm	MPA
Sparse-code multiple access	SCMA
Multi-user shared access	MUSA
Pattern division multiple access	PDMA
User activity detection	UAD
Compressive Sensing	CS
User 1	U1

User 2	U2
Joint-user activity identification and channel estimation	JUICE
Orthogonal Matching Pursuit	OMP
Adaptive subspace pursuit	ASP
Detection error rate	DER
Subspace matching pursuit	SMP
Symbol correcting mechanism	SCM
Least square estimation	LSE
Sequence Block Compressed Sensing Multi-User Detection	SB-CSMUD
Internet of things	IoT
Bit Error Rate	BER
Quadrature Phase Shift Keying	QPSK
Binary Phase Shift Keying	BPSK
Restricted isometric property	RIP
Matching Pursuit	MP
Group Orthogonal Matching Pursuit	GOMP
Orthogonal Least Square	OLS
Orthogonal Frequency-Division Multiplexing	OFDM
Internet service providers	ISP

Chapter 1

INTRODUCTION

1.1 5G Communication, An Overview:

Journey Wireless technology from 1G to 4G was evolving in terms of data capacity, data rates and key performance indicators (KPIs). 1G to 3G poor voice quality, battery life issues were there which were better addressed in 4G by enhancement in data rates. These technologies were specially designed for human type communication.

As Statistics indicate approximately 500 billion mobile users worldwide by 2025 [1]. Serious challenges arise which were faster data rates, greater coverage, reliable cloud connectivity, critical connections for industrial automation and most importantly how to connect a massive number of devices [2]. 5G was launched in 2016 [6]. It can provide downloading speeds up to 20 Gbps [7]. Besides being faster than existing networks, 5G can provide human-to-machine and machine-to-machine communication [4].

There are three main use cases of 5G communication which are Extreme Mobile, Broadband (eMBB), Ultra-Reliable Low Latency Communication (URLLC) and Massive Machine Type Communication (mMTC) [10]

1.2 Massive Machine-Type Communication, An Overview:

With the emerging revolution in science and technology, as well as industrial variations around the world, there is an increase in the growth of new challenges and requirements caused by the development of innovative applications, new markets and fields. advanced in mobile communication. mMTC has emerged as the most important service in 5G technology that has attracted sufficient interest from researchers. Basically, mMTC operates on sporadic activity and low data rates, which is different from Human Type Communication (HTC). There are many applications of mMTC in the market, including logistics, smart cities, smart grids, monitoring, etc. A huge increase in connected devices is estimated in the future and their expected number will reach 500 billion by 2024 [3]. Due to the substantial growth of these devices, mMTC faces many challenges to meet the performance requirements, such as low power consumption, high bandwidth efficiency, and massive connectivity. LTE offers security, mobility and global coverage, its performance is extremely inefficient to handle mMTC traffic [4]. Additionally, LTE operates at higher data rates and has high control signalling overhead to transmit small data packets. Conversely, mMTC requires low signalling overhead for small data packets to be transmitted sporadically. This research study attempts to increase the overloading capability of NOMA in CSMUD for mMTC in 5G communication technologies.

1.3 Non-Orthogonal Multiple Access (NOMA):

So far Orthogonal Multiple Access (OMA) schemes have served the users with the allocation of their orthogonal resources. OMA serves a single user in a single time slot or resource block and because of the orthogonality constraint, they are incapable of accommodating a huge number of users with limited resources [5]. Therefore, the performance criterion of 5G communication is not achievable through OMA schemes. However, NOMA schemes perfectly apply to the challenging requirement of spectrum scarcity in 5G technology by tackling massive connectivity with limited resources. The question is, how it can be applied to overcome these challenges? NOMA scheme allows more users to share the same available resource by transmitting their data simultaneously over the same channel. This can only be attained by using user-specific signatures while transmitting and receiving data. In a multi-user detection scheme, the non-orthogonal sequences assigned to specific users on the transmitting side are exploited by the reception device on the receiving end. Usually, devices are bound with scheduling requests to transmit their data, however, to see the potential of handling massive connectivity, researchers also considered NOMA for grant-free transmission. NOMA enables grant-free transmission in mMTC and allows the devices to send their data whenever they want without the bound of scheduling requests. Not only limited to mMTC, according to the existing surveys, but they also utilize its potential in typical HTC scenarios as well which are grant-based and the system parameters are already defined in the scheduling phase. In recent literature, many variants of the NOMA principle have been proposed based on its two fundamental categories: the power-based or power domain NOMA and the code-based or code domain NOMA.

1.3.1 Power-Domain NOMA:

In the power domain NOMA (PD-NOMA), the power of different levels is allocated to different users as their signatures [6]. These allocations are based on the distances between the base station (BS) and the users and they carried these power levels for detection at the receiver using successive-interference cancellation (SIC) [7]. In 2013, the idea of the PD-NOMA was introduced by the authors in [8], in which multiple users were allowed to simultaneously share frequency and time resources, thereby enhancing the spectral efficiency of the wireless networks. Figure 1.1 illustrates a typical 2-user downlink scenario of NOMA scheme. As can be seen, User 1 (U1) is the strong user having high channel gain as it is in the closest vicinity of the base station. The other user, U2, is at greater distance from the BS and is considered a weak user having low channel gain. Because of a shorter path loss, low power is allocated to the stronger user by the transmitter. On the contrary, a greater path loss favours the weak user for the allocation of more power from the transmitter. The size of the rectangle in Fig. 1.1 indicates the different levels of user-specific power allocations. At the receiving end of the strong user, successive interference cancellation is performed. Prior to the acquisition of its signal, the strong user decodes and subtract the signal of the weak user, which has a high signal-to-noise power ratio (SNR) at the receiving end of the strong user. In contrast, the weak user hand does not perform SIC as it considers the strong user signal to be a noise due to its low transmission power. Therefore, weak user receiver directly decodes its own signal [9]. In an uplink scenario

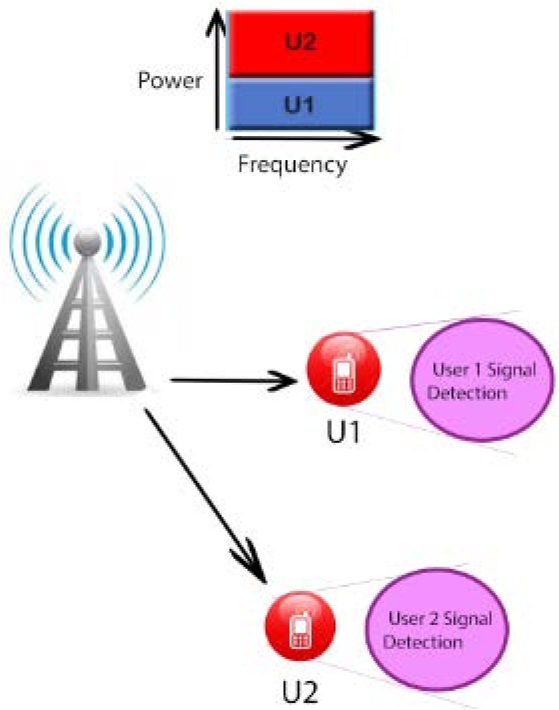


Figure 1.1: Basic two-user system model of power-domain NOMA

1.3.2 Code-Domain NOMA:

Code domain is the second main category of NOMA schemes, in which multiple users share the same time and frequency resources by using adopting unique spreading sequences. Although the concept is inspired by the typical code division multiple access (CDMA), however, there is a difference in the code-domain NOMA and CDMA as CDNOMA uses non-orthogonal, sparse low cross-correlated spreading sequences [11]. Two main components are used at the receiver of a code-domain NOMA system, i.e., SIC for separating users and message passing algorithm (MPA) technique for multiple user detection [12]. Figure 2.1 shows a block diagram of CD-NOMA uplink scenario.

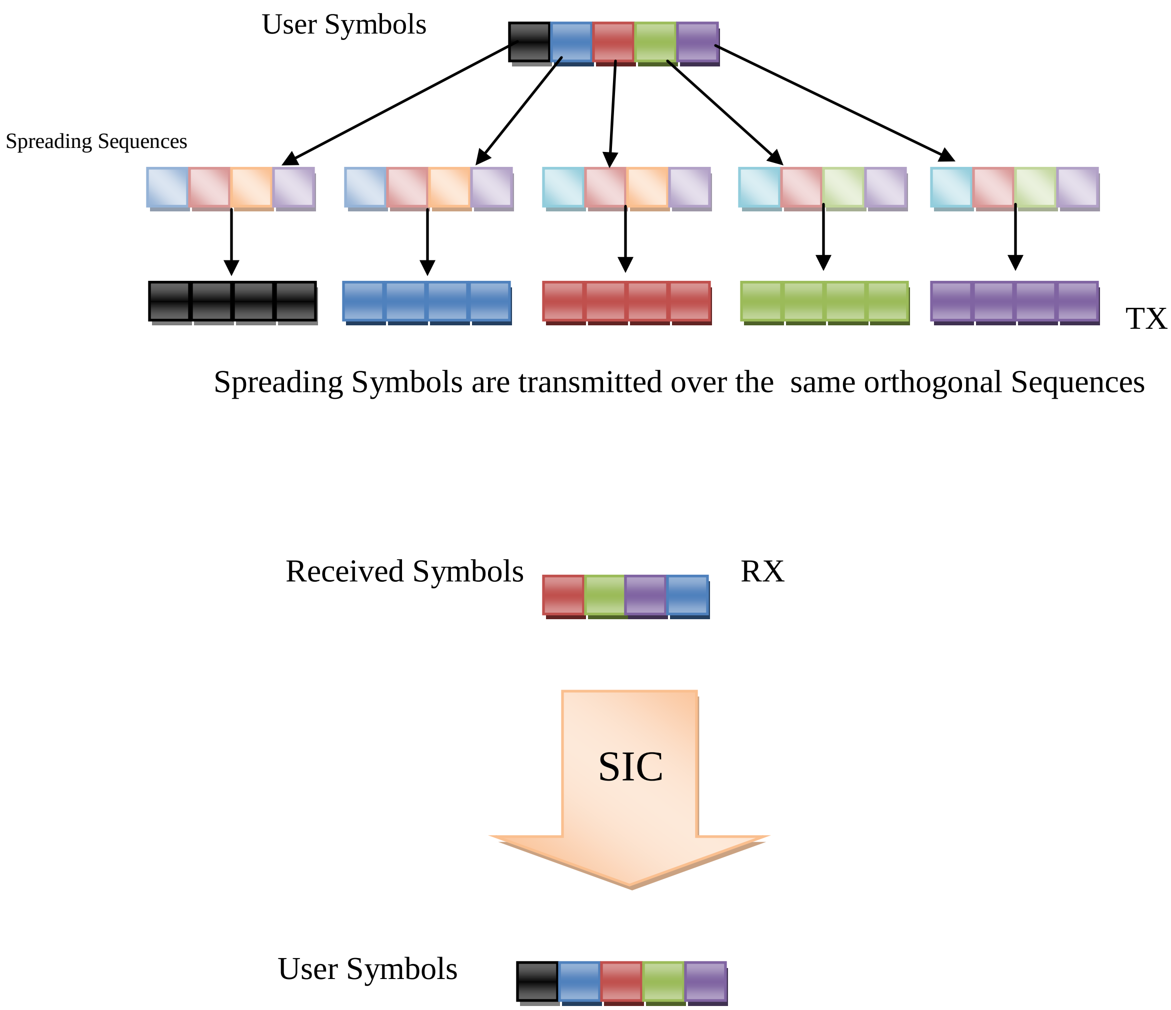


Figure 1.2: Code-Domain NOMA uplink scenario

1.3.2.1 Variants of Code-Domain NOMA:

Some alternates of code-based NOMA have been proposed in the existing literature. In [13], sparse-code multiple access (SCMA) is proposed. In [14], the authors introduced a multi-user shared access (MUSA) based CD-NOMA. In [15], the study has developed a pattern division multiple access (PDMA) scheme. SCMA technique such as MPA for multi-user detection at receiver and information bit stream is mapped to sparse codewords which are user specific directly after channel coding at the transmitter side. MUSA scheme exploits spreading sequences which are low correlated by assigning them to different users and supports SIC at the receiving end to detect multiple users [16]. At the PDMA transmitter, the signals from users are allocated in particular resource space, such as code domain, frequency domain, or spatial domain, and exploited effectively at the receiver to improve the performance of SIC detectors. Codewords are allocated by variety of non-zero elements according to the state of the user's channel [17]. In [18] Wang, Y et. al. performed the user activity detection (UAD) in uplink NOMA by using time invariant multi-path delay with a typical compressive sensing (CS) algorithm known as orthogonal matching pursuit (OMP) for channel estimation.

1.4 An overview of Compressed Sensing Multi-User Detection (CSMUD):

To overcome the challenges evolving in the field of mMTC, compressed sensing based multi-user detection (CSMUD) serves as a fundamentally intellectual approach. It exploits the sporadic transmission of mMTC for the estimation of received sparse signals of multiple users. CSMUD is mainly responsible for the joint detection of user data and user identification (activity) which provide ease in reliable reconstruction. In [21] and [22], Bockelmann et. al. proposed CS-based multi-user detection technique to address mMTC's future challenges. It takes the sparse nature provided by the CS theory to solve the underdetermined system of linear equations as well as to attenuate the effect of correlation between non-orthogonal spreading sequences [23]. In cross-correlation, the performance of the CSMUD is directly affected by the detection error rate (DER) of the system. Low correlated sequences will result in a low DER and vice versa [26]. In [24], Wu Liantao et. al. proposed a novel framework to enable efficient multi-user detection known as joint-user activity identification and channel estimation (JUICE). The proposed work jointly integrates the frame sparsity transmission and multi-antenna reception in up-link NOMA system. In the JUICE technique, two main mechanisms are involved in which the first one deals with the user's multiple access related to the process of CS measurement and the second one deals with the multi-user detection related to the process of user signal reconstruction. For efficient multi-user detection, the authors developed an enhanced subspace pursuit based greedy algorithm named as adaptive subspace pursuit (ASP), based on the spatial-temporal structure of the active users. OMP is used in CSMUD for detection at the receiver. It recovers the signal iteratively by picking a column from the sensing matrix which is highly correlated to the residual. Primarily, a residual is the received signal which is updated iteratively by subtracting the previous detection. After that, the method of least square estimation (LSE) is used to estimate the corresponding data. The orthogonality in OMP results in not to choose an index repeatedly because of orthogonality between the selected column vector and the residual. In [25], Shuo et. al. proposed a CS detector for up-link NOMA where symbols and indices of the active users are efficiently and separately detected. The authors designed low complexity subspace matching pursuit (SMP) for detecting the indices of the active users through which initial estimated symbol vector is obtained. After detection, a mechanism for symbol correction is introduced named as symbol correcting mechanism (SCM) for correcting and finding the errors faced in the initial results.

1.4.1 An overview of Sequence Block Compressed Sensing Multi-User Detection:

CSMUD was the scheme in which single sequence was assigned to single user and that sequence act as signature of that user but in SB-CSMUD whole sequence block assigned to one user which act as signature of that user. Sequence blocks are designed such a way that each user has a unique sequence. Maximum mutual correlation between sequence blocks is the basis of activity detection instead of correlation between sequences. The maximum correlation between signature of users become smaller because correlations are averaged over spreading sequences which are present in block.

1.5 Problem Formulation:

To accommodate a maximum number of devices, CS-MUD facilitates grant-free CD-NOMA where users are served by their non-orthogonal signature sequences which are assigned to them. However, spreading sequences come with an important factor, i.e., correlation between different sequences, which directly affects the detection of user identification (activity). Based on the limited availability of resources, when we increase the number of devices/users, the CSMUD system performance degrades due to high correlation. In order to control the coherence factor, the length of the spreading sequences or spreading factor may play a significant role as the correlation between the spreading sequences is a function of their length (or spreading factor). In [23] the SB-CSMUD scheme is introduced, in this technique whole code block is assign to each user so by taking mean correlation reduces and ultimately DER and BER also reduces and hence by comparing results we find that SB-CSMD is more efficient technique than CSMD. But problem is that code blocks are equal to the number of users. Results are very good so it means that we can increase the number of devices without increase the number of available resources.

This thesis Increases the overloading capability of NOMA with Sequence Block Compressed Sensing Multiuser Detection in 5G Communication.

1.5.1 Problem Statement:

The problem is how to increase theoverloading capability of NOMA with SB-CSMUD in 5G Communication without an increase of the number of available resources.

1.6 Statement of Goal:

Although the current SB-CSMUD schemes have reached a certain level of advancement, still their development is limited by the conditions experienced in many practical applications. For example, for data compression and acquisition there are a greater number of users and we are running out of resources, so the goal of the proposed research is to increase the overloading capability without increasing the number of spreading codes.

1.7 Summary of Contribution:

Contributions are represented with the help of block diagram in figure 1.3. First two and last two blocks in figure 1.3 the process is same which author has done in [70]. In which first author has done channel coding of all devices present in network. In second step Interleaving is done. During interleaving the message symbols are organized over more than one code blocks with the aid of using the interleaver earlier than sending over network channels. Due to this, lengthy burst noise sequences are unfolded out amongst more than one blocks. After interleaving author was applying QPSK modulation scheme on active nodes but to increase the overloading capability this thesis changes the modulation scheme from QPSK to BPSK. After modulation the modulated signal spread. In spreading the symbols of each group are spread over the corresponding spreading sequences in the node specific sequence block and then finally spreading sequences are then transmitted using orthogonal frequency division multiplexing.

For overloaded devices we have done following steps in this thesis. Firstly, we have done cannel coding of additional devices After FEC we have done interleaving same as author has done in [70]. After interleaving we have done modulation but this time, we do not apply BPSK. We apply rotated BPSK which is 90° phase difference of BPSK. After applying modulation, it goes in process of spreading. In spreading we assign them code blocks from within available resources but code blocks should be unique for each device. So, in this way all additional devices codes would become different from our initial devices but additional devices codes will overlap with few initial devices. This will affect DER performance. To tackle this, issue this paper has divided all number of initial devices into different groups. In each group not more than 50% devices become active at one time. For Example, S^1, S^2, S^3 and S^4 are in one group if S^1 and S^2 are active then S^3 and S^4 should not be active during that time. There are number of application where we can apply this technique and without disturbing DER and BER. Finally spread signal frames are then transmitted using OFDM.

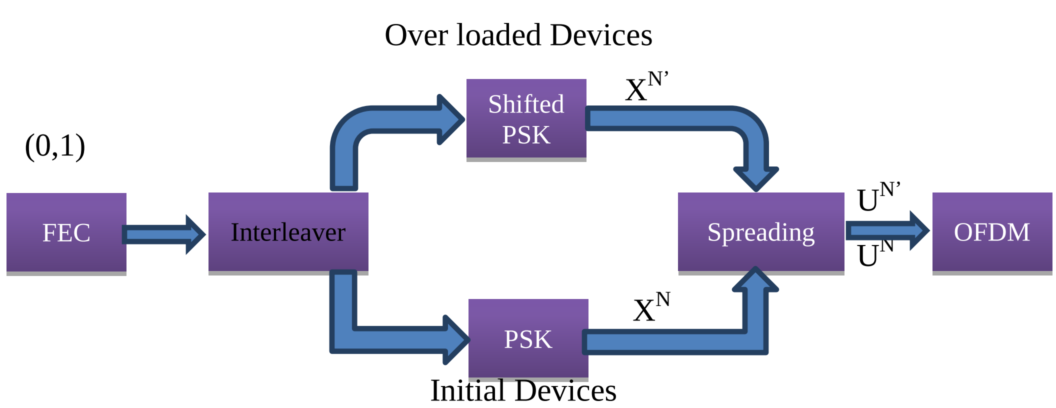


Figure 1. 3: Proposed Methodology

1.8 Application:

As we discussed earlier in 1.6 when we increase the overloading capability of NOMA with Sequence Block Compressed Sensing Multiuser Detection in 5G Communication the overloaded devices can become active only when those initial devices whose sequences are using by overloaded devices are not active during that time. Within that limitation Compressive sensing-based Internet of things (IoT) enables a variety of innovative services spanning manufacturing, healthcare, different every day human activities and smart cities. Many self-powered smart gadgets collect real-time data to exchange information and deliver services by communicating with each other and in addition to with the cloud. The reliability of data transmission and efficient consumption of power are the key factors to determine the performance of these self-powered IoT nodes. Therefore, different compression techniques have to be discovered for optimum data transmission. Compressive sensing is a novel theory in which the sparse behavior of the most real-world signals as well as IoT architectures is utilized to attain real-time platforms that are power efficient and can allow efficient applications of IoT [30].

1.8.1 Health care

In the health care sector, when we increase overloading capability of NOMA in SB-CSMUD is beneficial for a wide range of applications, such as pathology testing, medical laboratory and in medical testing. It also improves health monitoring platforms by making it cheaper, smaller and energy efficient [31]. For example, UV-C LED bore sanitization system use to sterilize medical imaging machines like MRI, CT, PET machines. The UV-C LED Bore Sanitization System was specially designed to clean any imaging bore (60-70 cm wide) and table (up to 200 cm long) with a kill rate of 99.9% in less than 5 minutes. Protect your patients and staff, reduce anxiety and easily bring a guaranteed image feeling to every patient, at all times [32]. During sanitization process these MRI, CT, PET machines should be in off state. In figure 1.4 twelve devices of two hospitals are connected to base station. Devices in red color are active, devices in black color are not active and devices in pale red are active overloaded devices. In Hospital A, device 1 is MRI machine, device 2 is CT-Scanning machine, device 3 and device 4 is UV-C LED Bore Sanitization System and device in pale red is fire alarm. Device 1,2,3 and 4 are in one group. Devices 3 and 4 depends upon device 1 and 2. Devices 3 and 4 cannot be active if any of the other two devices are active. So they will not affect fire alarm. In this way, we can increase overloading capability without increase number of resources. Another application in health sector is neuro department MRI room. In MRI room of neuro department patient comes who are suffering from different brain disorders. Those sensitive patients' need mental rest there should not be flickering lights like TV screen, there should not be noisy environment like music or ringing. So, while doing MRI of patient all devices which can produce flickering lights and cause noise should be turn off. As in figure 1.4 in Hospital B, device 5 is television, device 6 and 7 are MRI machines, device 8 is alarm and pale red device is camera. Device 5 and 8 depends upon device 6 and 7. When device 5 and 6 is active then device 6 and 7 can't be active. Device 5,6,7 and 8 are in same group. So, we can add an overloaded device without increasing of resources. Another application in health sector is in hospital Ophthalmology department. In Hospital B, Device 9 and 10 are VisuMax, Device 11 is LDV Z8 Machine, Device 12 is LDV Z6 Machine and Device in pale red is LDV Z4 Machine. These machines are used in eye laser surgery. According to surgery one from LDV Z8 or LDV Z6 or LDV Z4 is used with VisuMax in laser eye surgery. During surgery only one machine can be active at a time. VisuMax depends upon those devices when they are not active then VisuMax can active. Device 9,10,11 and 12 are in same group. So, we can add another machine device which could be LDV Z4 machine to make process more quick. All devices are connected with the base station doctor can easily perform surgery so in this way, we can increase overloading capability without increase number of resources.

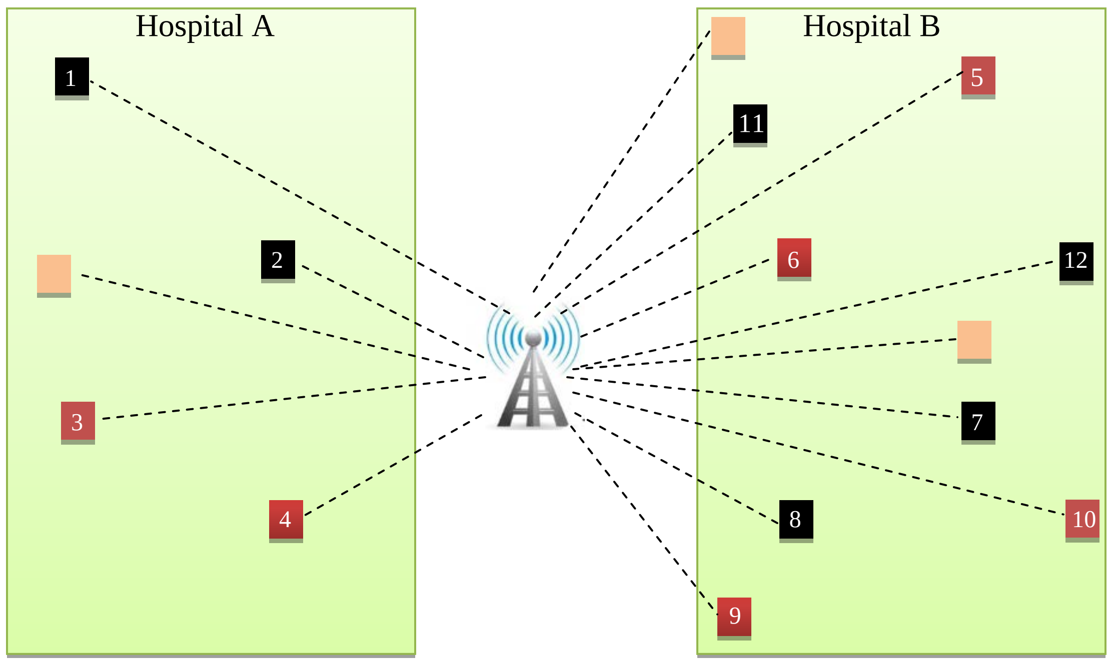


Figure 1. 4: Twelve IoT devices of two hospitals are connected with base station

1.8.2 Outdoor

A pyranometer is a device that is used to measure the solar radiation flux density and solar irradiance on a planar surface [34]. It is use in various places like agricultural weather networks, ecological weather networks, hydrological weather networks, solar panel arrays and many other. As it uses to measure the solar radiation flux density so it can active during day time. On the other hand, street lights can active only during night time. Scenario of day time is shown in figure 1.5. Device in red color is active and devices are in black not active and device in pale red is active overloaded device. Devices 1 and 2 are street lights and devices 3 and 4 are pyranometer. All devices are connected to base station and they all are in one group. Device 3 and 4 depends upon device 1 and 2. Due to their different functions if 1 and 2 are active then 3 and 4 should be not active and vice versa. So we can add one extra device which could be temperature sensor. So, in this way, we can increase overloading capability without increase number of resources.

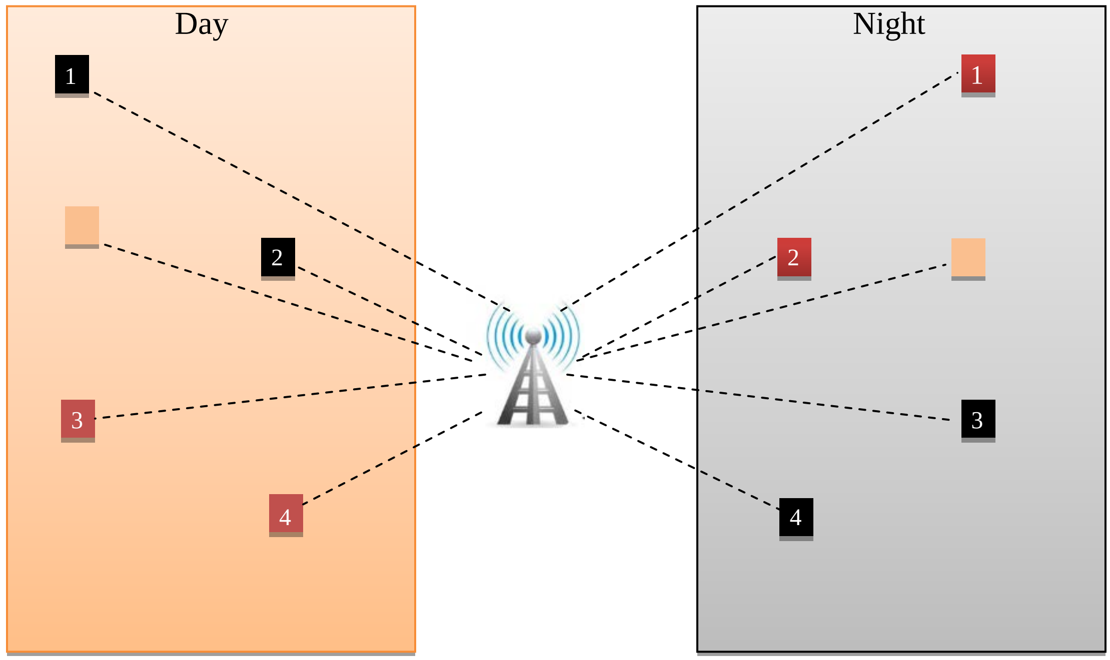


Figure 1. 5: Four outdoor IoT devices connected with base station

1.8.3 Indoor

Indoor is associated with smart-home applications. Home appliances use in winter like electric heater, electric geyser, electric instant geyser, electric banket, boiler etc. These devices can active only in winter season but during summer people use home appliances like electric sealing fan, pedestal fan, chiller, AC, inverter, water dispenser etc. So, in group we can add 50% devices of one season and 50% devices of other season.

In figure 1.6 we can see the scenario during summer and winter. Devices is red are active, devices in black are not active and device in pale red is active overloaded device. Device 1 is electric heater, Device 2 is electric geyser, Device 3 is chiller, Device 4 is electric fan, and overloaded device is electric fridge. Device 1,2,3 and 4 are in one group. In summer device 3 and device 4 are active and device 1 and device 2 are not active but in winter devices 1 and device 2 are active and device 3 and device 4 are not active. So these devices will not affect overloaded device. So, in this way we can increase overloading capability without increase number of resources.

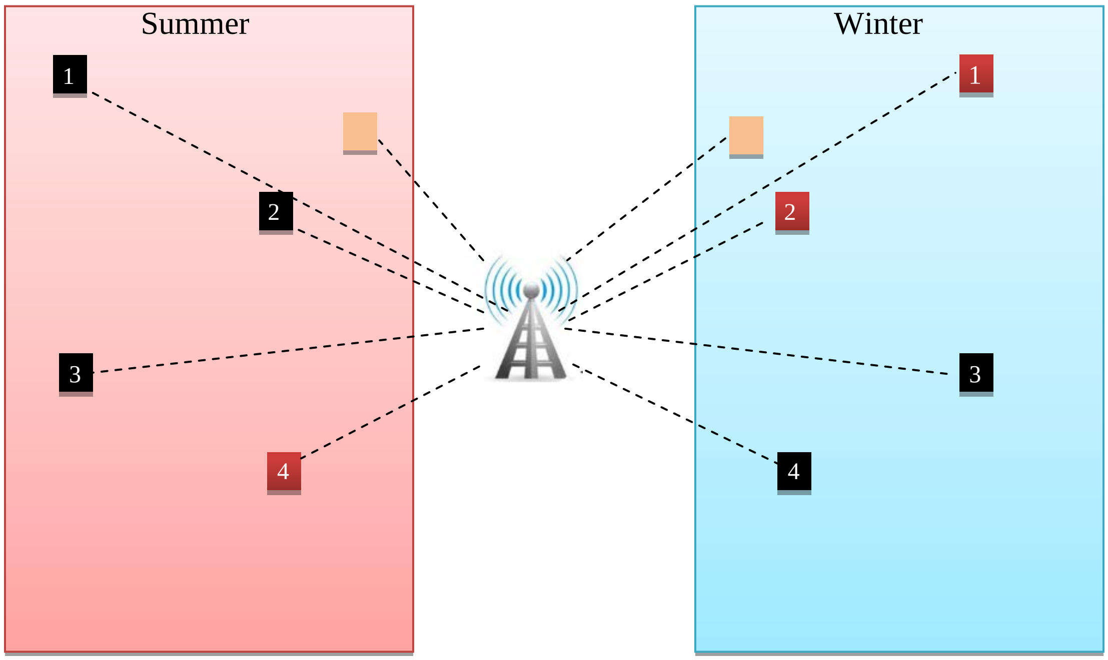


Figure 1. 6: Four indoor devices connected with base station during summer and winter season

1.8.3 Industrial Automation

In industries, the control systems and automation mainly rely on various industrial sensors to precisely perform different processes. There are number of plants which requires continuous electric supply from smart grids. During electricity breakdown portable generator can turns on automatically and supply power to plant. So, we can make automatic portable generator as an overloaded device because it can active only when there is an electricity breakdown.

1.8.4 Others

Other application includes logistics, distributed signal processing, channel estimation and ultra-wide band communication. All these descriptions of how CS applications could be used in our daily lives and in all cases we can overload number of devices.

1.9 Thesis Outline:

There are five chapter of this thesis. Chapter 1, justifies the importance and overviews of different techniques which are using in this theses. Objective, Summary of contribution and application of proposed technique are also discussed. Chapter 2 briefly discussed the related work which has done in near past. Chapter 3 explains the proposed model consisting of pre-processing techniques. Chapter 4 presents simulation results where conventional and proposed results are compared with one another by using different number of devices. Chapter 5 summarizes the thesis work along with future recommendation.

Chapter 2

LITERATURE REVIEW

2.1 Compressed Sensing (CS):

The idea of deed and exploiting entire quantity of information was finished as shortly because the compressed sensing was introduced. The development of the information works on discarding most of the info that is acquired without any perceptual loss. In signal processing, the compressed sensing is the techniques in which sparse signals are sampled at a much lower rate than the Nyquist rate as maintain in [36]. Consider there is a signal x and x is K-sparse for K << N. x $\in C^{N\times 1}$ when there are only K non-zero elements. There is a basis function Φ which is assume to be a sparse signal. In the form of its basis function Φ the signal x can be represented. Consider z = Φx be a compressible signal with reference to Φ. The CS generates y $\in C^{M\times 1}$ by a measurement matrix Ψ $\in C^{M\times N}$ K < M < N. The signal is given below as:

$$\mathbf{y} = \mathbf{\Psi\Phi x} + \mathbf{n} \,, \tag{2.1}$$

Where the background noise is denoted by vector n $\in C^{N\times 1}$. A sparse vector x is required to be determined for the recovery of vector x, which satisfies the equation 2.1. Optimization techniques are used as it is an underdetermined system of linear equations to solve the system in Equation 2.1. Subject to y = ΨΦx + n, the vector x is written in mathematical form as:

$$\hat{\mathbf{x}} = arg \min_{\mathbf{x}\in\mathbb{C}^{N\times 1}} ||\mathbf{x}||_0 \,, \tag{2.2}$$

where x represents the estimated signal and $\| \cdot \|_0$ represents the L_0 norm. L_0 Norm essentially offers the variety of the non-0 elements of vector x. To solve Equation 2.2, distinctive algorithms and relaxation procedures may be followed such as L1 norm this L1 norm is used in basis pursuit de-noising [37].

2.2 Recovery of Signal Via L1 optimization:

Minimization of L_1 norm is the reconstruction through L_1 optimization. Minimization of L_1 norm is commonly use in compressive sensing [38]. It is one of the convex-optimization issues wherein an underdetermined system of linear equations is solved and the desired signal is recovered with better accuracy, having cubic order complexity

2.3 Recovery of Signal Via Orthogonal Matching Pursuit Algorithm:

In the approximation theory, for sparse reconstructions the OMP algorithm is used which also called greedy algorithm [39]. Basically, modified version of matching pursuit (MP) is the OMP and in terms of complexity it is still the simplest of all the algorithms [40] [41]. Using Orthogonal Matching Pursuit, the x Is iteratively recovered through selecting one of these columns from the sensing matrix which demonstrates excessive correlation with the residual with inside the system. Basically, the initially received signal is the residual, this is up to date in each generation through subtracting it from the preceding detection. The estimation of corresponding information is accomplished the usage of the least square estimation after attaining assist of x. Due to the orthogonality present in OMP, it'll in no way select the index again and again because the residual and the chosen column vector are orthogonal to every other.

2.4 Sensing Matrix:

For the recovery or non-recovery of a sparse vector x from a measurement vector y several factors are associated for example vector x itself is sparse in nature, the sensing matrix A which comprised of the channel coefficients and the spreading sequences and the algorithm used to recover sparse vector x. These factors are mutually dependent, as a result in lots of applications we've got manage best at the measurement processes or whether the recuperation of the sparse vector x with an algorithm may be accomplished successfully. restricted isometric property (RIP) is the one of the properties of sensing matrix used in the compressed sensing analysis is a well-known property introduced in [42].

2.4.1 Restricted Isometry Property (RIP):

Sufficient condition for actual or approximate reconstruction of sparse signal representation s from the y measurements is offered in RIP. There is a sensing matrix A belongs to CM×L that satisfies the restricted isometric property of order K when the restricted isometric property constant exists is given as:

$$(1-\delta)||\mathbf{s}||_2^2 \leq ||\mathbf{s}||_2^2 \leq (1+\delta)||\mathbf{s}||_2^2 \, , \tag{2.3}$$

Where $||s||_0$ is equals to K and δ_k is restricted isometric property constant belongs to (0, 1). From the value of δ_k the solution of linear equation **A**x = y is analyzed, the degree of deviation from the non-uniqueness of the solution is shown by the lower value of δ_k. Degree of isometry of the sensing matrix operation on its K columns is measured by the RIP. in the case of a sensing matrix, it is difficult for RIP to prove whether or not it meets the condition. Mainly random matrices, including Bernoulli matrix, matrices with i.d inputs satisfying the RIP and Gaussian matrix [43].

2.4.2 Mutual Coherence:

One of the key parameters to determine the performance of sensing matrix in CSMUD is the mutual coherence [44]. It is relatively simple and feasible property of sensing matrix [45]. In addition, in the defined sensing matrix Ψ it serves as the largest absolute value of correlation between all the columns, which can be determined as:

$$\mu_{max} = \max_{1 \leq i \neq j \leq N} \Psi_i^T \Psi_j \tag{2.4}$$

ith column in the sensing matrix Ψ is Ψ_i. If the condition of sparsity is satisfied, the true support of the signal can be fully recovered by a matrix which is shown in [46].

$$K \leq \frac{1}{2}\left(\frac{1}{\mu_{max}} + 1\right) \, , \tag{2.5}$$

Where active nodes or supportable non-zero elements are represented by K. When μ_{max} increases, K decreases and when μ_{max} decreases, K increases. It is also been mentioned in [47] [48], that mutual coherence guarantees the acceptable performance.

2.5 Compressed Sensing Multi-User Detection:

CSMUD jointly detect user activity and user data. The data estimation of the corresponding node is done at the receiver when active node is detected by least square estimation. Mathematically, the overall Bit Error Rate of the system is computed as:

$$BER = \frac{\xi L + (K - \xi)\gamma}{N\ L}\ , \qquad (2.6)$$

Where γ shows the number of errors while detecting activity, K denotes the number of active nodes, ξ denotes the average number of errors and L denotes the data frame length. BER depends on both data and activity detection which is shown by the Equation 2.6.

2.6 CSMUD Algorithms:

As in mMTC, CSMUD introduces sparsity and it exploit the sparsity so different algorithms in CSMUD have been proposed. The multi-user detection (MUD) technique can be classified into two groups: maximum a posteriori probability (MAP) based algorithms and greedy algorithms.

2.7 Greedy Algorithms:

The higher complexity in case of sphere decoding based algorithm and the convex optimization restricts their deployment in the environment of mMTC. To overcome this issue of complexity, greedy algorithms were proposed for CSMUD which reduces the complexity of MUD.

2.7.1 OMP and OLS:

OMP and OLS based algorithms for multiuser detection has introduced by authors in [56]. Active users which are most probable then estimate their data subsequently have been iteratively taken by these algorithms. For both the algorithms i-e OMP and OLS, the information is known at the base station that spreading matrix **S** has the influence in the sensing matrix **A**. At its every iteration OMP algorithm selects the column which is highly correlated with the received signal from sensing matrix **A** and also detects the corresponding user is active. On the other hand, in OLS the selection is instead of correlations is based on the minimum least square distance. Although OMP is least efficient to errors as compared to OLS but complexity rate is high in OLS. However, the greedy algorithms may experience error propagation as they estimate the data and activity iteratively.

2.7.2 Block-OLS and group-OMP:

Activity detection of CSMUD has improved by block OLS and the modification of greedy algorithms into group OMP. By taking advantage of the fact that a node can transmit several bits in the single frame when it displays it is active. Then it outputs the frame of the multi-user signal as a sparse block [4] [55]. In [55] the advancement of orthogonal least squares to block wise OLS is introduced, in block wise OLS active user is detected for the block of symbols being transmitted. The detection of activity depends on the sum of minimum Euclidean distance between spreading sequences from the block of N_d symbols at the receiver. In [4] The extended OMP for CSMUD is introduced which is called group orthogonal matching pursuit (GOMP). In group orthogonal matching pursuit, the selection criteria are based on spreading sequences and sum of correlations of received symbols N_d instead of selecting single highly correlated column with single received symbol. Due to this proposed selection criteria the activity detection is improved. The matrix inversion in case of GOMP increases the complexity for larger N_d therefore the frame is split into sub-frames and also to avoid this issue parallel detectors are used to detect the signal at receiver side. And also, Viterbi decoder is used to reduce false alarms an activity aware although these alarms are less critical than miss detection. Actually, Viterbi decoder take decisions on the activity of user because it is more a decision device. Further, for improved detection an extension of GOMP has introduced in [57] which is known as weighted GOMP based algorithm (wGOMP) [57]. Channel decoder generated weights in weighted GOMP [57],

$$w_j = 0.5 + \frac{\xi_C(\hat{d}_k) - \xi_\epsilon(\hat{d}_k)}{2N_d} \quad \forall j \in \Gamma(k) \tag{2.7}$$

Where this ξ_ϵ (d_k) = $\|d_k\|_2$ indicates that node k is active, $\Gamma(k)$ consists of indices of vector related to group k, Euclidean distance of the codeword is represented by $\xi_C(d_k)$

and Vector's length d is represented by "Nd". The weights are multiplied with correlation after the selection step of GOMP in weighted GOMP which enhances the activity detection and by implementing weighted GOMP algorithm the symbol error rate (SER) is improved relatively with GOMP by magnitude of one [57]. The authors proposed considered MMV-CS model and algorithm SOMP and in [58]. The algorithm simultaneous orthogonal matching pursuit detects the support for a set of symbols and is similar to group orthogonal matching pursuit. For the entire frame sparsity is expected to remain same.

2.7.3 Iterative order recursive least square:

GOMP has a limitation of complexity but on the other hand it improves the detection performance for CS-MUD. Along with the size of the group the GOMP complexity increases exponentially. Recursive least square (IORLS) based algorithm is introduced to overcome this limitation the iterative order, IORLS makes the higher complexity minimum which associate with the length of the frame as mention in [59]. To prevent from group computations and correlations the IORLS iteratively uses the orthogonal matching pursuit algorithm. By weight multiplication 'W0 with the selected matrix based on the correlations between received signal and sequences the node selection criteria of orthogonal matching pursuit algorithm are improved. Actually, the weight matrix is a diagonal matrix having Wn entries, where n is the number of sequences from 2 to N-1 for which the n−th column is detected as active in the iteration which is iterated previously. Moreover, for further reduction in complexity the OMP matrix inversion switched to order recursive least square. It is observed that the complexity of IORLS unlike the GOMP increases linearly with number of iterations and its performance is based on the iteration numbers as well as frame length.

2.7.4 Structured Matching Pursuit (SMP):

A node is active for a number of consecutive symbols this is the general belief of sparsity exploiting algorithms. However, some nodes may be active in in mega machine type communication for fewer symbols and some of them are active for a number of consecutive symbols. Therefore, within the frame duration set of active nodes varies. The authors considered the structured sparsity in multiuser signal for improved multi user detection in [62] [61]. Common active users are defined as the active users are assume to remain active for several consecutive time slots. Dynamic active users are defined as activity of users changes for each time slot. Structured matching pursuit (SMP) based algorithm used for multi user detection. Structured matching pursuit firstly the detection of common active users is based on their sum of energies over time slots that are continuous. Its effect is subtracted from the residual, which is initially considered as received signal after the detection of common active users. After successfully detection of Common active users, Structured matching pursuit then detects the dynamic active users at every time slot by using the selection criteria of orthogonal matching pursuit. It can be seen from the proposed approach of detection the performance is enhanced by a magnitude of 1 at 3dB SNR [62]. The idea was modified in [61] to efficiently estimate the data in the user activity by exploiting this temporary correlation. In [61] Dynamic compressive based multi user detection algorithm detects the activity of users at symbol level and obtain support for one symbol which is used as primary support for the estimation of data on subsequent time slot. The proposed Structured matching pursuit, when it is compared to the conventional orthogonal matching pursuit it enhances the data estimation and overall performance.

2.7.5 Matrix Matching Pursuit (MMP):

Authors in [63], proposed the greedy algorithm named as matrix matching pursuit besides Matrix Matching Pursuit algorithm for detecting activity. Orthogonal matching pursuit is extended to Matrix Matching Pursuit algorithm in which active users are selected on the basis of highest correlation between spreading sequences and sample co-variance matrix φ_{YY} of received signal matrix Y. Mathematically φ_{YY} is written as

$$\phi_{YY} = \frac{1}{N_d} YY^H = SVS^H + \phi_{WW} \qquad (2.8)$$

Where φ_{WW} represents the sample noise co-variance matrix, S shows the spreading matrix and $V = E(DD^H)$ is the transmitted co-variance matrix of multiuser frame. The m−th user is active if the m−th element of diagonal matrix V is 1. In [63] authors also discussed the MMV-CS model to increase computation speed and reduce the receiver complexity. Moreover, the proposed matrix matching pursuit gives improved activity detection along with the constant complexity to the frame length. However, all the proposed algorithms in [63] are used only for detecting activity and all has to be deployed data detection separately once the support is obtained. Further, the evaluation of overall performance is not considering the fading channel effect but it only involves the AWGN channel. Some of the performance evaluation parameters are considered also which in the context of mMTC are not the realistic for example, to consider a frame length of 1000 bits but the transmissions of mMTC are few bytes. Moreover, the activity probability in [63] is considered pa = 0.35 while it is $p < 0.1$ for mMTC for evaluating frame length effect.

2.8 Sequence Block Based Compressed Sensing Multi-User Detection:

By introducing the block of sequences authors proposed an advance technique of CSMUD in [69], for spreading the data. In SB-CSMUD, a block is considered which contains the spreading sequences as an alternative of single sequence. Instead of the single block, the performance of SB-CSMUD is analyzed from the largest mean coherence between the blocks of sequences. The lower the value of correlation, the lower will be the DER and vice versa. SB-CSMUD jointly detect user data and user activity and when active node is detected then data estimation of the corresponding node is done at the receiver by LSE.

2.8.1 Sequence Block Design and Formation:

In SB-CSMUD, a random sensing matrix is generated which contains the block of sequences. Sensing matrix is shown in figure. Each user in the network is assigned with a block of **D** sequences obtained from the generated sensing matrix $\mathbf{S} \in C^{M\times N}$. Sequences are selected randomly from the unit circle $s_i(\nu)\ \exp(2\pi\nu)$, where ν is uniformly distributed over an interval [0,1]. Once the sensing matrix consisting of the spreading sequences is generated, the blocks are formed using sliding window technique. Several other possible procedures can be used for blocks formation, however, herein we used the procedure based on sliding window technique. As **D** represents the size of the block, in Fig. 2.1 design of **D**=4 is shown.

$\mathbf{S^1}$ shows the first block of sensing matrix **S** which consists of first four spreading sequences $\mathbf{S^1}$ = [s_1, s_2, s_3, s_4]. Similarly, in the second block, the spreading sequences are $\mathbf{S^2}$ = [s_2, s_3, s_4, s_5] and so on till $\mathbf{S^N}$. $\mathbf{S^N}$ would be $\mathbf{S^N}$= [s_N, s_1, s_2, s_3]. In both the conventional CSMUD and SB-CSMUD, the total sequences remain the same. However, the requirement of memory is increased by an amount of **D** at the sensor node where the block of sequences is stored. Nonetheless, there is no significant difference in the computational complexity of both the SB-CSMUD and CSMUD schemes.

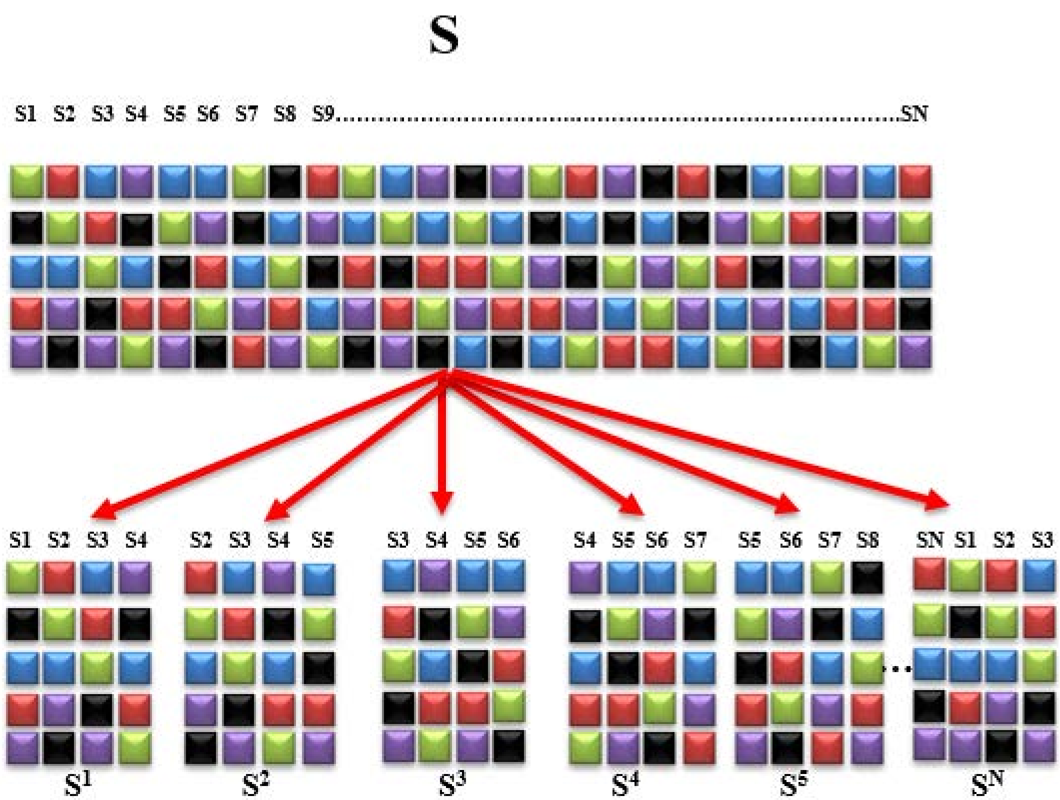


Figure 2. 1: Selection procedure of sequence blocks from sensing matrix

2.8.2 Processing at Sensor Node of SB-CSMUD:

Figure 2.2 illustrates the mechanism of signal processing at the sensor node. The modulation of signal after passing through forward error correction (FEC) coding scheme is performed through the quadrature phase-shift keying. The modulated signal in the data frame enters into the spreading block and uses the assigned sequences blocks for spreading. In the process of spreading, the symbol blocks of amount G = L/D are formed from the data frame. Using the sequence blocks defined specifically for the users, the spreading of these symbol blocks is performed. The first symbol is spread by using first index of sequence block and second is spread with second index and so on. In the end, the resulting frame of spread signals of all the nodes $U^n \in C^{M \times L}$ are transmitted by using orthogonal frequency-division multiplexing (OFDM) algorithm [69]. There are two types of models which serves as the basis of CSMUD scheme such as the single measurement vector (SMV) model and multiple measurement vector (MMV) model.

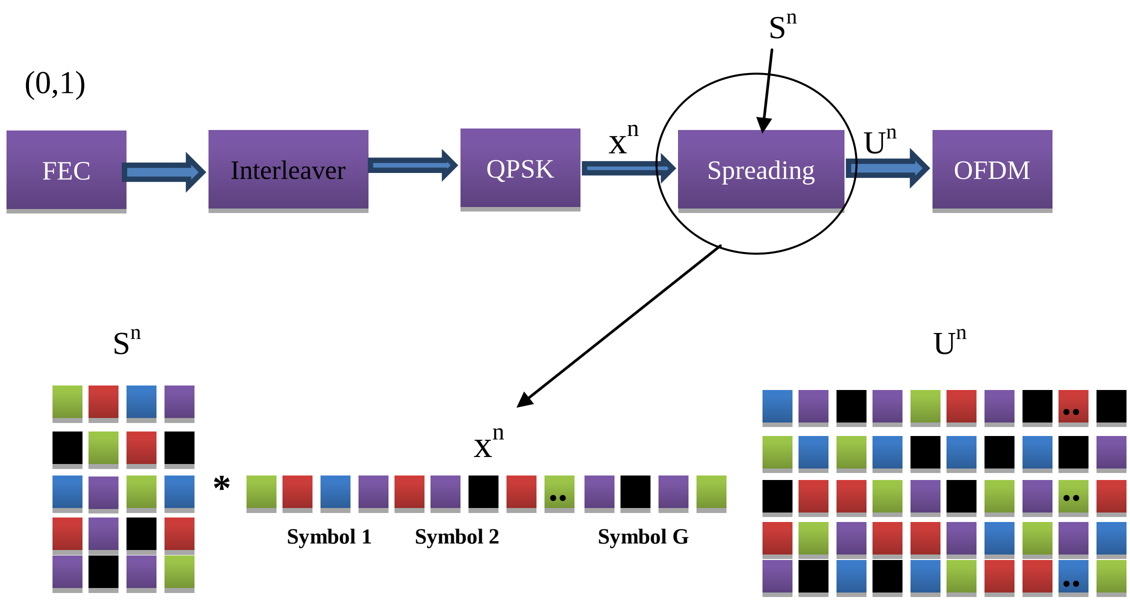


Figure 2. 2: Node processing follows the strategy of column-symbol multiplication in which the first column of S n matrix is multiplied with the first symbol in the symbol block of x n, the second column is multiplied with the second symbol and so on.

2.8.3 Single Measurement Vector (SMV):

With the growth and advancements in the field of compressive sensing, the researchers have been motivated to explore a number of extensions in the conventional problem of sparse signal recovery [64], in which the reconstruction of a few non-zero elements of the signal is performed through the small number of linear measurements that are incoherent. SMV model is one of the extensions in CSMUD. For every symbol, interval activity detection is performed in SMV problem which is formulated on symbol level. The received signal along with channel gain and AWGN noise is defined as,

$$Y = SHx + W = Ax + W \tag{2.9}$$

where S belongs to $C^{M \times N}$ and contains spreading sequences for N number of users, W is the Gaussian noise, H is a diagonal matrix belongs to $C^{N \times N}$ and it contains the information about user's channel coefficients, x is the composite signal belongs to $C^{N \times 1}$. Inactive users are represented by zero elements in the vector x. The matrix A belongs to $C^{M \times N}$ contains the combination of channel coefficient and spreading sequences and is known as sensing matrix. The CSMUD model based on SMV in a matrix form is depicted in Fig. 2.3.

2.8.4 Multiple Measurement Vector (MMV):

In MMV problem, the acquisition of measurement vectors set is performed through a set of jointly sparse signal vectors, in which a common support is shared. It has the following applications, direction-of-arrival estimation [65], magnetoencephalography [66], [67], and parallel magnetic resonance imaging (pMRI) [68]. At every iteration, mean correlation of the columns of sensing matrix with the received signal is used for activity detection and the corresponding data is estimated.

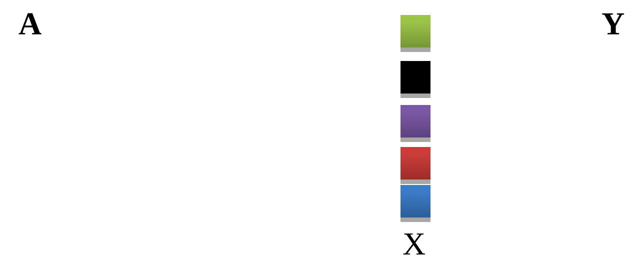


Figure 2. 3: NOMA's SMV-based CS model

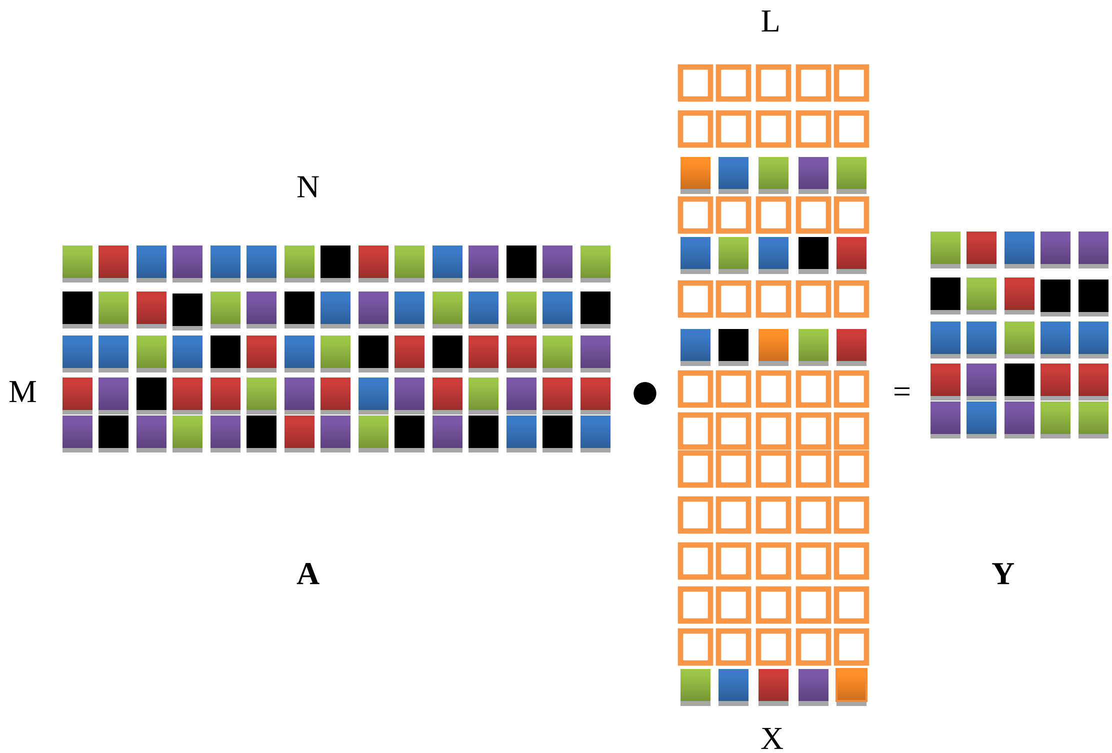


Figure 2. 4: MMV based CS model for NOMA

The received signal matrix of defined model is given as

$$
\begin{aligned}
Y &= SHX + W \\
&= AX + W
\end{aligned}
\tag{2.10}
$$

where, $X \in C$ $N \times L$, contains modulated symbols of all the users. As shown in Fig. 3.1, the rows of X represent the sequence of symbols from single user whereas the columns denote the symbols from N number of users at a time. Also rows with zeros in X matrix represents inactive users and W is a Gaussian noise belongs to C $M \times L$. In order to characterize the CSMUD as MMV model, the fact that an active node transmits more symbols at a time is utilized.

2.9 Comparison between existing techniques and proposed technique:

There are number of techniques proposed in near past which has mentioned in this section. If we see the latest model of SB-CSMUD which author has proposed in [70]. Results were excellent but limitation was author cannot overload devices because of modulation scheme. This thesis has increased overloading capability. So, now without increase of number of resources this thesis accommodates additional devices.

Chapter 3

PROPOSED MODEL

3.1 System Model:

In this study, mMTC scenario is considered in which N number of users sporadically access a single base station, as illustrated in Fig. 3.1. It is assumed that few number of nodes out of N nodes are simultaneously active and sending the data to the base station. In Fig. 3.1, red represents the active initial devices transmitting data frame of L symbols, pale red represents the active overloaded devices transmitting data frame of L symbols, black represents the inactive devices and are not transmitting any data and pale black represents the inactive initial devices and are not transmitting any data either. Each user in a unique spreading sequence for spreading their data based on non-orthogonal (multi-carrier) MC-CDMA and these sequences also act as signature for the devices. As high correlation

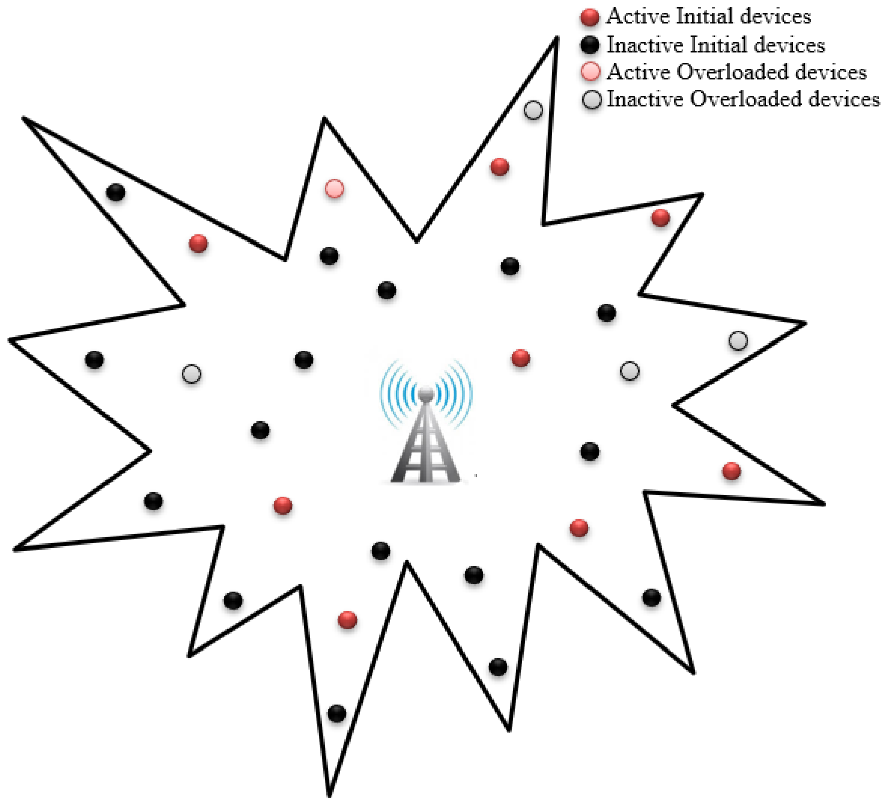


Figure 3. 1: mMTC: N represents the nodes that are connected to the BS

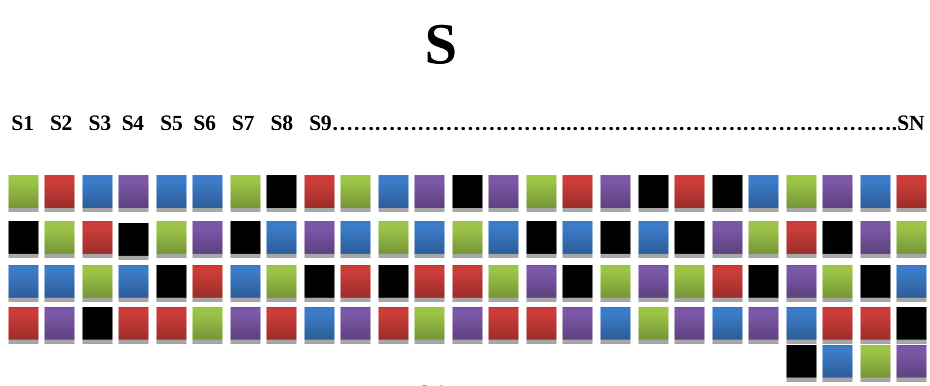
between the spreading sequences of MC-CDMA system is responsible for degraded performance, therefore, modified techniques of multi-user detection are required for such systems to improve signal reconstruction. The authors in [70], proposed an advance technique of CSMUD by introducing the block of sequences for spreading of data. In SB-CSMUD a block is considered containing spreading sequences as an alternative of single sequence. The largest mean coherence between the blocks of sequences is one of the parameters on which the performance of SB-CSMUD scheme is highly dependent. When the value of correlation is small, the DER will be lower and vice versa.

3.2 Deterministic Sensing Matrix for SB-CSMUD:

In SB-CSMUD, the sequence blocks are highly correlated with each other, though less than the single sequence-based signatures. The length of the spreading sequences/spreading factor also have an impact on the correlation. Higher the spreading factor, lower will be the maximum correlation between the sequences. However, spectrally it is inefficient to increase the length of the spreading sequences for achieving low correlation. To make these sequences mutually incoherent we proposed a model of deterministic sensing matrix to significantly reduce maximum correlation μmax, without changing the length of the spreading sequences. In SB-CSMUD, an active node transmits the data frame having L number of symbols, mod (L, D) = 0, in which the value of D represents the block size of the spreading sequences.

3.3 Sequence Block Design:

In SB-CSMUD, a random sensing matrix is generated which contains the block of sequences. The sequence block S = [s.(n+1), s.(n+2), · · ·, s.(n+D)], $0 \leq n \leq N$. Each user in the network is assigned with a block of D sequences obtained from the generated sensing matrix $S \in C\ M\times N$. Sequences are selected randomly from the unit circle si(ν) exp(2πν), where ν is uniformly distributed over an interval [0,1]. Once the sensing matrix consisting of the spreading sequences is generated, the blocks are formed using sliding window technique. Several other possible procedures can be used for blocks formation, however, herein we used the procedure based on sliding window technique. As D represents the size of the block, in Fig. 3.2 design of D = 4 is shown. S^1 shows the first block of sensing matrix S which consists of first four spreading sequences S^1 = [s1, s2, s3, s4]. Similarly, in the second block, the spreading sequences are S^2 = [s2, s3, s4, s5] and so on till N, S^N would be [sN, s1, s2, s3]. We have N blocks and without increasing spreading sequences we have to accommodate users till N’ so we have to assign them unique sequences first overloaded sequences are $S^{(N+1)}$ = [s1, s3, s5, s7]. Similarly, in the second block, the spreading sequences are $S^{(N+2)}$ = [s2, s4, s6, s8] and so on till N’, $S^{(N'+1)}$ would be [s(N’-6), s(N’-4), s(N’-2), s(N’)]. In SB-CSMUD, the total sequences remain the same. However, the requirement of memory is increased by an amount of D at the sensor node where the block of sequences is stored.



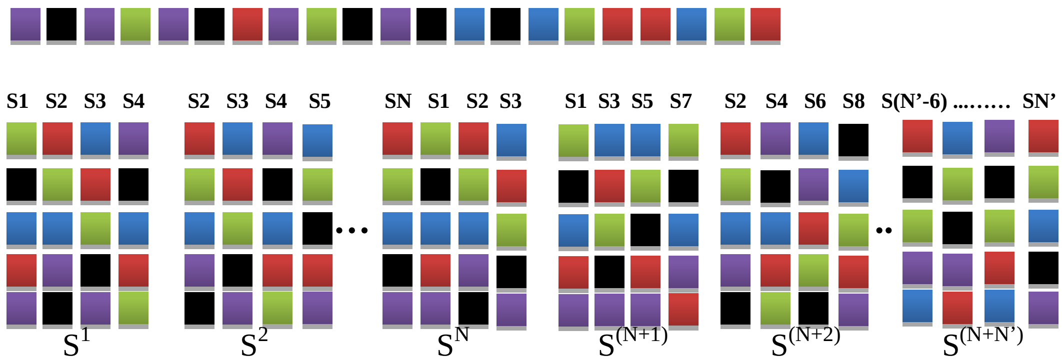


Figure 3. 2: Selection procedure of sequence blocks from sensing matrix (S)

3.3 Proposed Methodology:

From figure 3.2 blocks from 1 to N, is the work which has done in [70]. In which first author has done channel coding of all devices present in network. In second step Interleaving has done. After interleaving author was applying QPSK modulation scheme but to increase the overloading capability this thesis changes the modulation scheme from QPSK to BPSK that's why in figure 3.2 blocks are in green color. After modulation x^n modulated signal spread. The symbols of each group are spread over the corresponding spreading sequences in the node specific sequence block is shown in Figure 3.1, where the first symbol of each group spreads over the first sequence in the sequence block, the second symbol over the second sequence and so on. The resultant spread signal frames of all the N nodes $U^n \in C^{M\times L}$, $1 \leq n \leq N$, are then finally transmitted using OFDM. Figure 3.4 represents multiplication of first column of the S^n with first symbol of a symbol block of x^n, second column with second symbol and so on. In figure 3.3 blocks from N+1 to N' are the process of signal transmission of overloaded devices which we add without increasing number of resources. So firstly, we have done cannel coding of overloaded devices After FEC we have done interleaving same as author has done in [70]. After interleaving we have

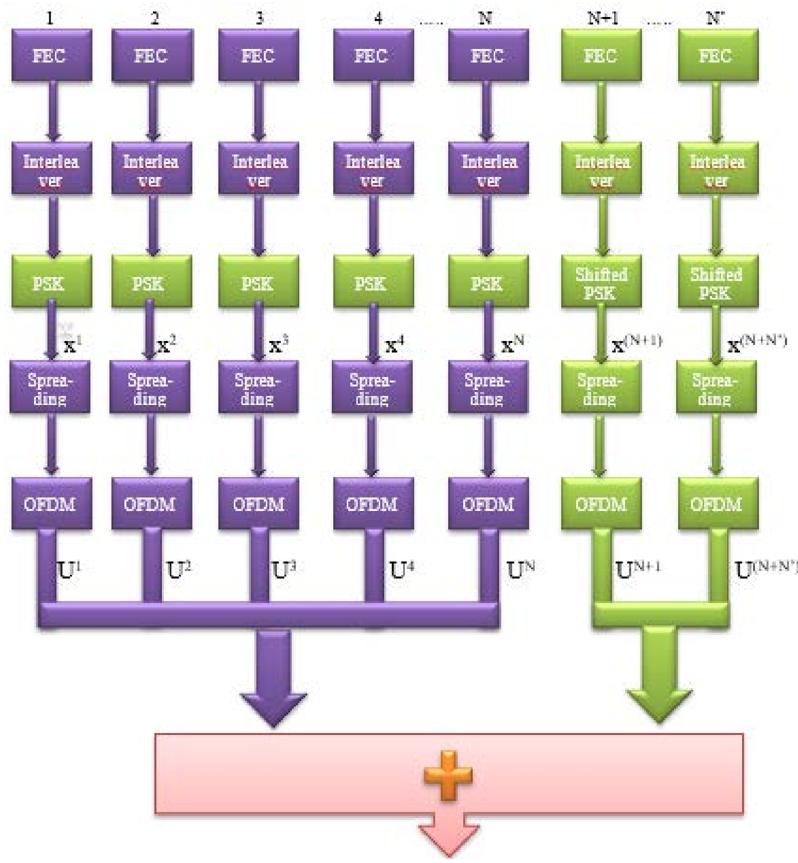


Figure 3. 3: Proposed Methodology

done modulation but this time, we apply rotated BPSK which is 90° phase difference of BPSK. After applying modulation, the modulated data frame $x^{n'}$ spread using the assigned sequence blocks from $S^{(N+1)}$ to $S^{(N+N')}$. In figure 3.2 as a whole $S^{(N+1)}$ to $S^{(N+N')}$ are unique. So, in this way all additional devices sequences would become different from our initial devices sequences but additional devices sequences will overlap with four initial devices spreading sequences. This will affect DER performance. To tackle this, issue this thesis has divided all number of initial devices into different groups. In each group four devices are present. In each group not more than two devices become active at one time. For Example, S^1, S^2, S^3 and S^4 are in one group if S^1 and S^2 are active then S^3 and S^4 should not be active during that time. Because sequence s_1 in S^1 and $S^{(N+1)}$, sequence s_2 in S^2 and $S^{(N+2)}$, sequence s_3 in S^3 and $S^{(N+3)}$ and sequence s_4 in S^4 and $S^{(N+4)}$ are in same position. The resultant spread signal frames $U^{n'}$ of all the overloaded N' nodes are then finally we transmit $U^{n'}$ spreading sequences by using OFDM. Figure 3.4

represents multiplication of first column of the S^n with first symbol of a symbol block of x^n, second column with second symbol and so on There are a lot of applications where we can apply this technique some of them are mention in 1.7.

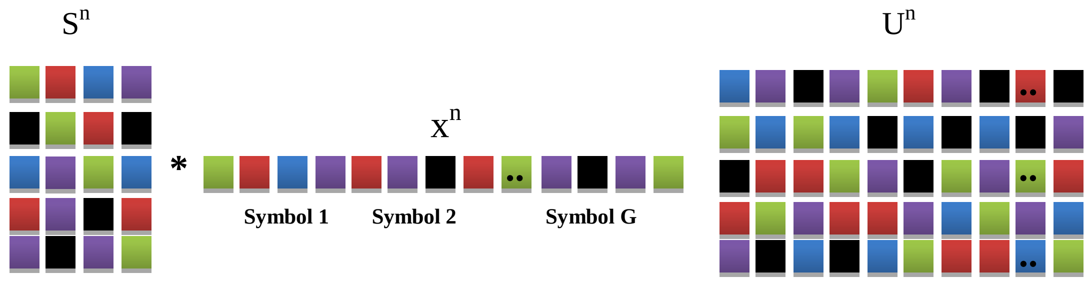


Figure 3. 4: Processing at node n, each symbol of x^n consists of 4 blocks

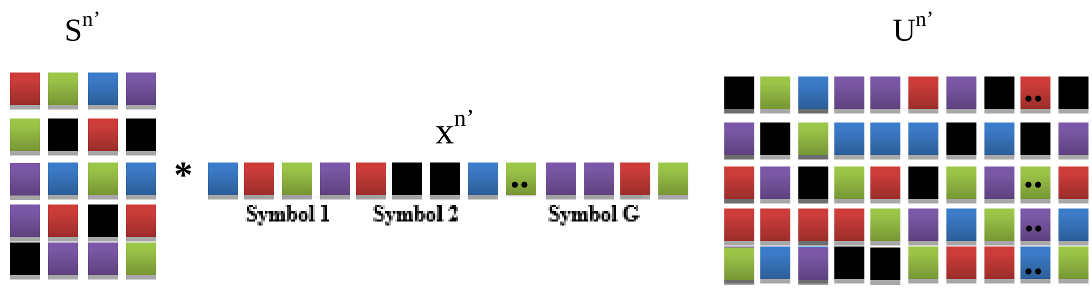


Figure 3. 5: Processing at node n, each symbol of x^n consists of 4 blocks

Chapter 4

RESULTS AND DISCUSSION

We have increased the overloading capability of NOMA in SB-CSMUD in 5G communication. By keeping matrix S constant, we accommodate 25% more nodes in network. After applying purposed technique, we have seen in results that BER and DER are decreasing exponentially. Number of nodes are denoted by N, number of active nodes are devoted by K. All parameters are given in table 4.1.

Table 1: Simulation Parameters

Number of Initial Nodes	I=100
Number of Overloaded Nodes	O=25,50,100
Number of Nodes	N=125.150,200
Spreading Factor	M=20
Active Users	K=12,16
Frame Length	L=32
Block Size	D=4
Modulation	BPSK & Shifted-BPSK
Activity ability	pa=0.1
Spreading Matrix	S=100

4.1: Overall Bit Error Rate:

In fig 4.1 BER is decreasing when SNR is increasing. There are 125 nodes. Red color line in graph is representing conventional I=125 nodes. Which means that there are 125 resources and 125 nodes so each node is using single sequence block. As we can see result is good BER is decreasing when SNR is increasing. So, we keep number of resources 100 and overload 25 more nodes. There are 100 initial nodes I=100 and 25 additional nodes O=25 and we can see blue line is representing this scenario in 4.1, BER of N=125 is also decreasing when SNR is increasing. Now we apply grouping, we divide all 100 initial nodes in group of four. In one group not more than two nodes become active at one time. Then we add 25 more users without increasing number of resources all initial nodes are in group of four devices. Magenta color line in figure 4.1 is representing this. Results are showing BER of N=125 with and without grouping is also decreasing when SNR is increasing hence BER results shows that by applying purposed technique we can increase the overloading capability.

In fig 4.2. There are 150 nodes. Green color line in graph is representing conventional I=125 nodes. Which means that there are 150 resources and 150 nodes so each node is using single sequence block. As we can see result is good BER is decreasing when SNR is increasing. So, we keep number of resources 100 and overload 50 more nodes. There are 100 initial nodes I=100 and 50 additional nodes O=50 and we can see magenta line is representing this scenario. Results are showing BER of N=150 with is also decreasing when SNR is increasing hence BER results shows that by applying purposed technique we can increase the overloading capability.

In fig 4.3 Now we are using 200 nodes. Green color line in graph is representing conventional I=200 nodes. Now keeping number of resources 100 and overload 100 more nodes. There are 100 initial nodes I=100 and 100 additional nodes O=25 and we can see magenta line is representing this scenario BER of N=200 is also decreasing when SNR is increasing. Results are showing BER of N=200 is also decreasing when SNR is increasing hence BER results shows that by applying purposed technique we can increase the overloading capability.

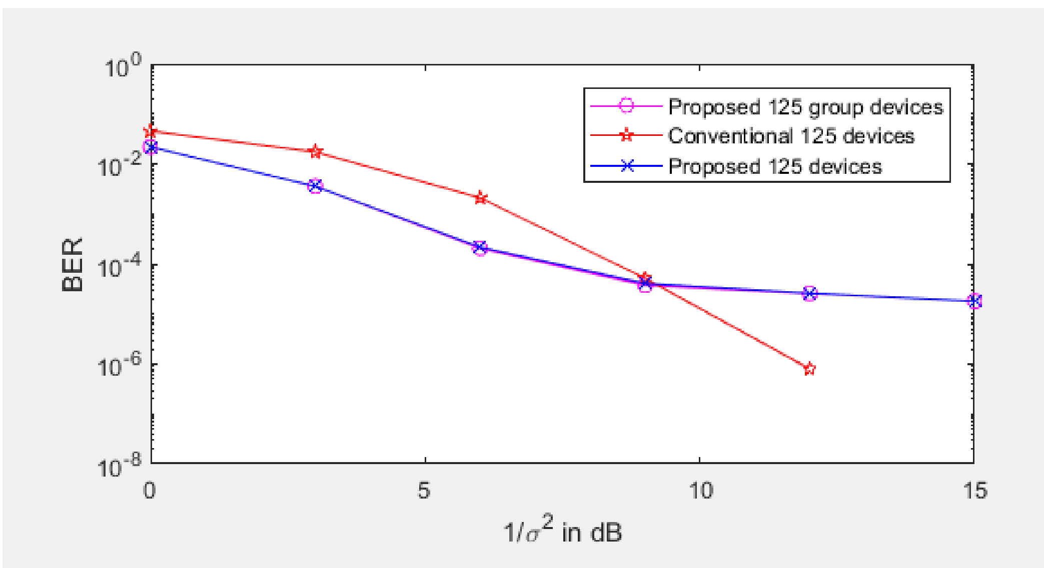


Figure 4. 1: BER performance comparison in NOMA SB-CSMUD by keeping S=125

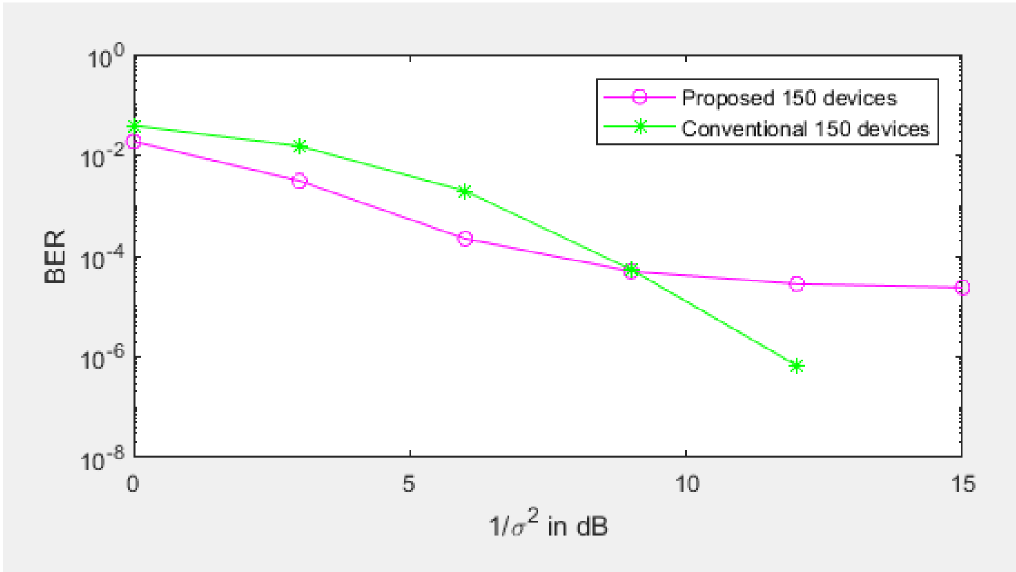


Figure 4. 2: BER performance comparison in NOMA SB-CSMUD by keeping S=150

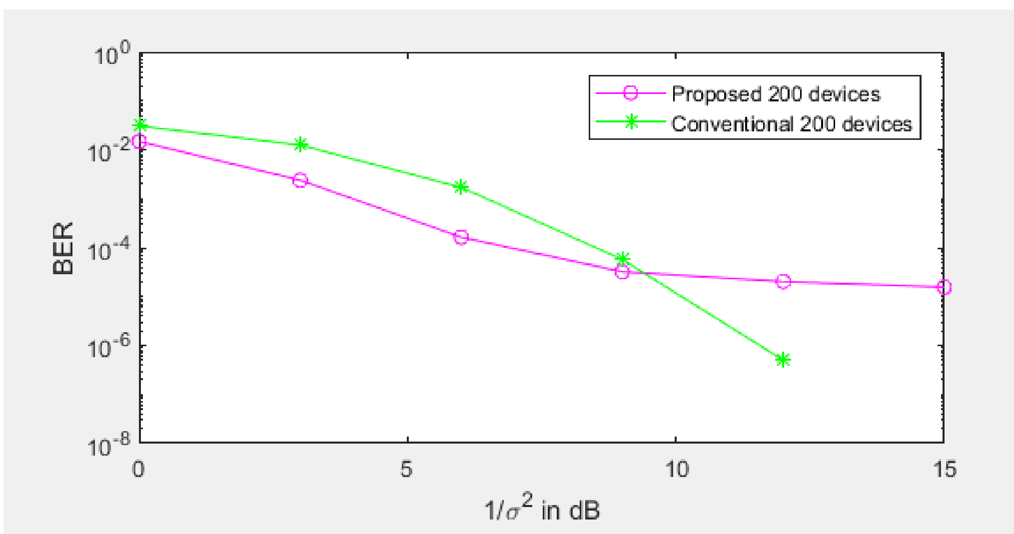


Figure 4. 3: BER performance comparison in NOMA SB-CSMUD by keeping S=125

4.2 Miss Detection Rate:

In fig 4.4 MDR is decreasing when SNR is increasing. There are 125 nodes. Red color line in graph is representing conventional I=125 nodes. Which means that there are 125 resources and 125 nodes so each node is using single sequence block. As we can see the result is good MDR is decreasing when SNR is increasing. So, we keep a number of resources 100 and overload 25 more nodes. There are 100 initial nodes I=100 and 25 additional nodes O=25 and we can see blue line is representing this scenario in 4.4. Results of proposed technique is better than existing technique. Now we apply grouping, we divide all 100 initial nodes in group of four. In one group not more than two nodes become active at one time. Then we add 25 more users without increasing number of resources all initial nodes are in group of four devices. Now results becomes better magenta color line in figure 4.4 is representing this. Results are showing by applying purposed technique we can increase the overloading capability.

In fig 4.5. There are 150 nodes. Green color line in graph is representing conventional I=125 nodes. Which means that there are 150 resources and 150 nodes so each node is using single sequence block. As we can see result is good. DER is decreasing when SNR is increasing. So, we keep number of resources 100 and overload 50 more nodes. There are 100 initial nodes I=100 and 50 additional nodes O=50 and we can see magenta line is representing this scenario. Results are showing DER of N=150 with our proposed technique is far better than existing technique. Hence DER results shows that by applying purposed technique we can increase the overloading capability.

In fig 4.3 Now we are using 200 nodes. Green color line in graph is representing conventional I=200 nodes. Now keeping number of resources 100 and overload 100 more nodes. There are 100 initial nodes I=100 and 100 additional nodes O=100 and magenta line is representing our proposed technique. By comparing both we can see our proposed technique is far better than existing technique. hence DER results shows that by applying purposed technique we can increase the overloading capability.

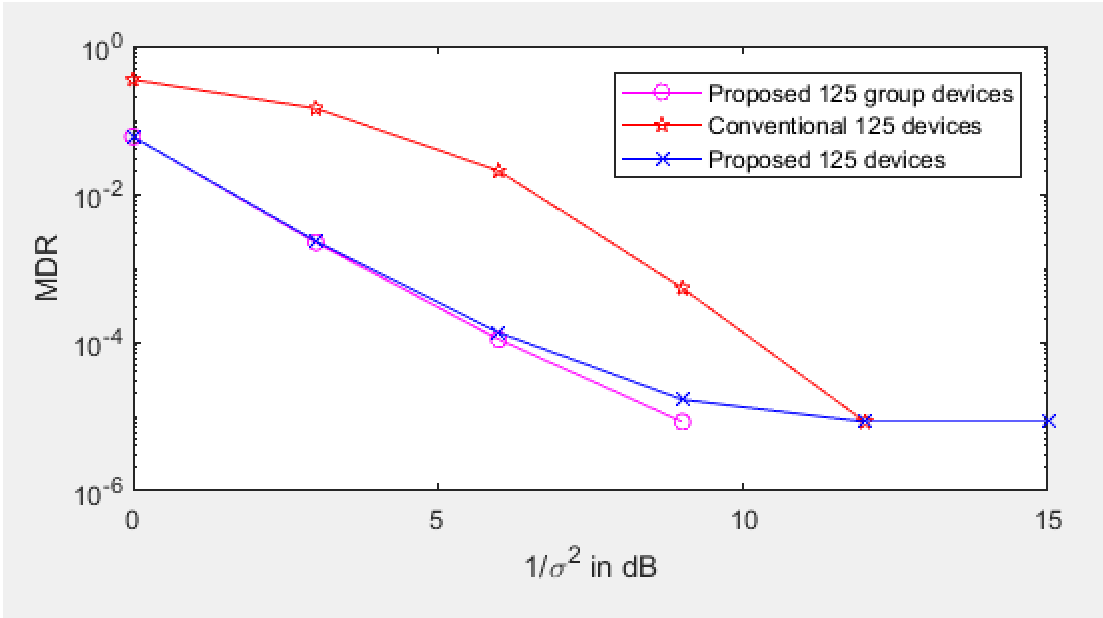


Figure 4.4: MDR performance comparison in NOMA SB-CSMUD by keeping S=125

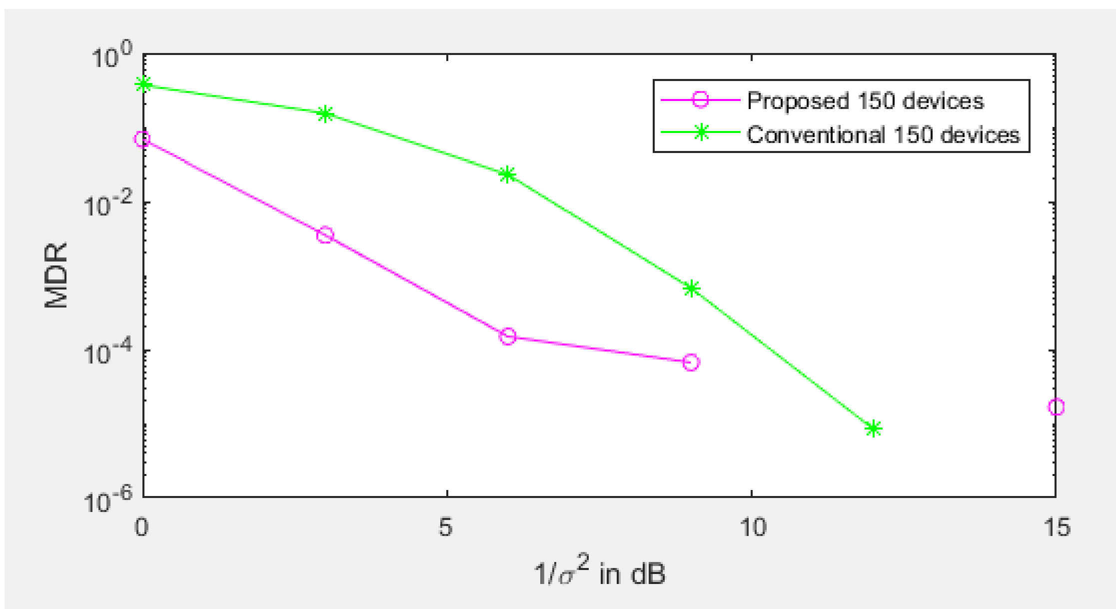


Figure 4.5: MDR performance comparison in NOMA SB-CSMUD by keeping S=150

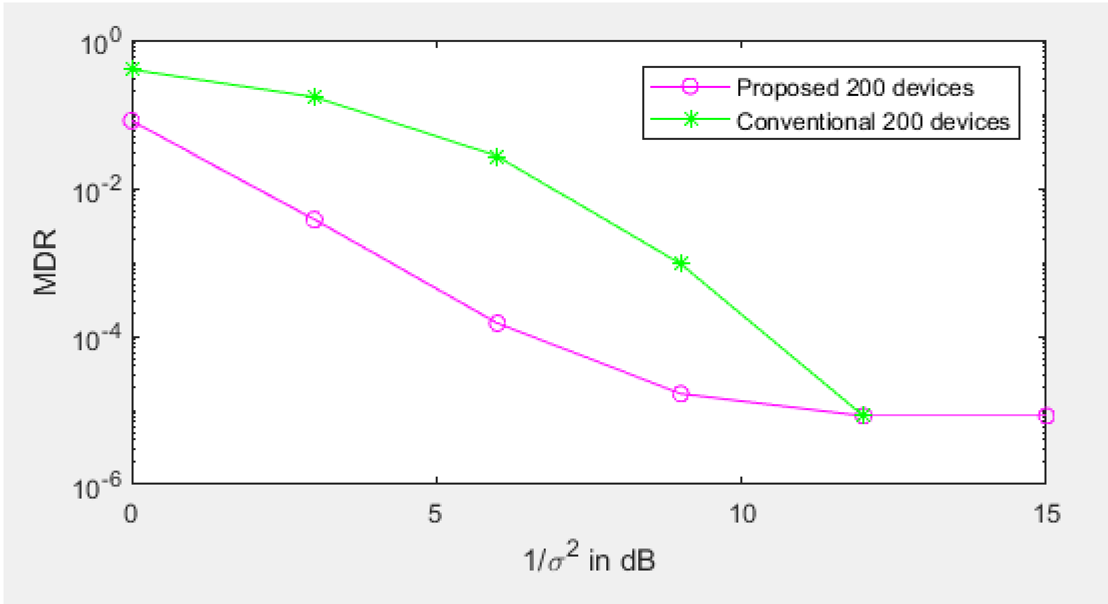


Figure 4.6: MDR performance comparison in NOMA SB-CSMUD by keeping S=200

From figure 4.1 to 4.6 proved that our purposed technique is correct and we have increased the overloading capability of NOMA of SB-CSMUD in 5G communication.

Chapter 5

CONCLUSION AND FUTURE WORK

The simulation results of the proposed model were seen in the previous chapter. So, the outcomes of the proposed method and potential future work are discussed in this chapter.

5.1 Conclusion

In this research study we propose new approach to increase overloading capability of SB-CSMUD. This purposed a model which efficiently detect data and activity of all devices present in the network and accommodates more active users simultaneously without increasing the spreading factor. The activity is dependent upon the correlation between sequences. Devices having more correlation are supposed to be active devices. All initial devices are not independent devices. All initial devices are divided in different groups in each group only 50% devices can active at one time. The proposed design significantly improves the performance.

5.2 Future Work

In [71] separation of QoS between mMTC devices on 5G has been done. The purposed technique can also further be differentiated the QoS among different devices by repeated transmission. Furthermore, BER should be improve.

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