**Engineering and Technology Journal e-ISSN: 2456-3358**

**Volume 09 Issue 05 May-2024, Page No.- 3909-3921**

**DOI: 10.47191/etj/v9i05.06, I.F. – 8.227**



# Developing Laboratory Experiments to teach Undergraduate Engineering Students Multi-User Massive MIMO Technology for 5G Cellular Networks

**Mussawir Ahmad Hosany[1], Surfaly Bibi Shadiihah[2]**

[1,2]Department of Electrical and Electronic Engineering, Faculty of Engineering, University of Mauritius

**ABSTRACT:** An effective method of facilitating student learning in a laboratory environment is "practice by doing". The study of modules related to signal-processing for digital communications requires deep mathematical and theoretical foundations but the practice goal is not really emphasized in the undergraduate curriculum at the University of Mauritius. This causes the students to lose interest in the corresponding modules resulting in high rate of failures. In this work, we propose to develop laboratory experiments with a view to bridge the gap between theoretical and practical aspects in the field of Massive Multiple-Input Multiple-Output (MIMO) systems for 5G cellular networks. Various laboratory scenarios are set up that consider a Maximum Ratio Combining (MRC) receiver in the uplink with an uncorrelated Rayleigh fading channel. Moreover, from a signal processing perspective to enhance the student's understanding, we analyze the efficiency and error performance of Massive MIMO systems with MPSK and MQAM modulation schemes as well as perfect and imperfect channel estimates. The leading industry software package MATLAB R2022 is used to develop all laboratory experiments and the codes are elaborated in this analysis. Data collected from the experiments are used to generate spectral efficiency and error performance curves which can be used for future research. The findings underscore the significance of accounting for both scenarios and illuminate promising avenues for future research in the realm of massive MIMO education and learning. The assimilation of MATLAB® flowcharts for each MRC receiver, MPSK, and MQAM with perfect and imperfect Channel State Information (CSI) adds further depth to the study, ensuring a comprehensive understanding of the intricacies of massive MIMO systems. Ultimately, this contribution helps in the nurturing of expertise such that future generations of wireless communication pioneers can be inspire.

**KEYWORDS:** Massive MIMO in Education, computer science education, Remote Labs, MRC receivers, Channel State Information (Perfect and Imperfect), Rayleigh fading channel

## I. INTRODUCTION

Based on the objectives set for 5G cellular systems higher spectral as well as energy efficiencies are expected and therefore novel technology components such as Massive MIMO, Ultra-dense and reliable networks, device-to-device communications and M2M have to be implemented [1]. The Massive Multiple-Input Multiple-Output (MIMO) system, for 5G cellular networks, is where a number of user terminals are served by massive Base Station (BS) antennas using the same time-frequency interval [2]. According to [3] expressions were derived for the non-cooperative Signal to Interference and Noise Ratio (SINR) values whereby a number of BS antennas tend to infinity. Thus, the effects such as uncorrelated noise, fast fading, and intra-cell interference are neglected. Inter-cell interference, resulting from reverse-link pilot sequences reuse however limits the performance. Additionally, advanced network MIMO Time Division Duplex systems that allow the collaboration between base stations and outer multi-cellular precoding methods have been suggested to aid in the alleviation of multi-cell Interference [4]. The opportunities gained from the Massive MIMO technology are the increased system capacity, besides having a higher ability to transmit huge amounts of data over a frequency spectrum. It also uses energy resources to effectively perform a task in a communication system. As compared to the cellular base station, the number of antennas used in wireless MIMO is larger. With increased spectral and energy efficiency, transmissions, both uplink and downlink are enhanced. Upon making use of multiplexed spatial signals, the system capacity can be increased. A large antenna array can be used to illustrate the BS precoding capability. Moreover, several studies have been conducted that evaluate the spectral efficiency of very large arrays of antennas and these analyses have focused on the educational aspects in a laboratory setting for teaching in undergraduate programmes [5]. It is better to have a base station having multiple antennas as compared to a single one. Also, if a base station serves many user terminals, a linear doubling effect of spectral capacity will be seen. Thus, the capacity is also enhanced [6].

In addition, a massive MIMO can be built by using components consuming low power. Hence, less amount of energy is required, reducing costs. The individual antenna elements, found in antenna arrays use less power, in the range of milliwatts [6]. When power is curbed, the system service quality improves, as transmit power increases [3]. In this paper, the Multi-User Massive MIMO system is set up as various laboratory experiments for undergraduate engineering students. The major objectives of the experiments are outlined as follows:

1. Design and implement new massive MIMO systems under perfect and imperfect channel state conditions using MATLAB Software.
2. Evaluate the bit error performances under various digital modulation schemes.
3. Evaluate the average throughput of the MIMO systems under various channel estimates.
4. Extend the design of the experimental setup for future research work.

In order to address the above-mentioned objectives new experiments and projects are added in the Communications Laboratory at the Department of Electrical and Electronic Engineering of the University of Mauritius. These will enable capacity building and the students can build competencies in the concept of Massive MIMO technologies in terms of theoretical and practical aspects. The paper is organized as follows: Section 2 describes the basics of Massive MIMO systems with emphasis on efficiency and error performance when employing a Maximum Ratio Combining (MRC) receiver. The proposed methodology to set up the various laboratory experiments are elaborated in section 3 and the entire implementation procedure as well as all detailed experiments are presented in section 4. Output results of all experiments are graphically illustrated and described in section 5 and the paper is concluded in section 6 with some future research works outlined.

## II. BASICS OF MULTI-USER MASSIVE MIMO FOR 5G CELLULAR NETWORKS

Massive MIMO employing MRC receivers needs a favorable propagation environment. If the channel cannot respond from a base station to different terminals, it becomes problematic. The use of large arrays in determining channel behavior is not the same as that used with smaller arrays, since large fading might occur [2]. Wireless networks play a crucial role in modern communication systems where they are applied in diverse cases. There exist different Wi-Fi standards (802.11a, the 802.11b, 802,11n, 802.11ac, and 802.11ax) which provide wireless connectivity in a local area network. Moreover, the deployment of Massive MIMO in a Wi-Fi network system may be subjected to interference and noise. In the presence of spectrum congestion, the performance of both Wi-Fi networks and Massive MIMO MRC systems is degraded. Thus, there is a need for spectrum allocation and resource management, such that efficient coexistence between both can be ensured. This is normally done by regulatory bodies where spectrum resources are carefully managed, avoiding interference and ensuring the optimized performance of the wireless technologies.

Also, advanced MRC techniques Massive MIMO when used in dense areas, provide improved reliability and throughput of the Wi-Fi communications. However, integrating Wi-Fi networks and Massive MIMO MRC systems has some loopholes that can be overcome by further research. For instance, some of the mechanisms include algorithm optimization and protocols that can ensure that Wi-Fi and Massive MIMO MRC systems can coexist. If these problems are addressed, then one can benefit from both technologies, for improved network capabilities and catering for the well-being of society.

In the field of Telecommunications, MRC is a technique whereby signals from different channels are combined. It involves a series of steps, among which, there are addition of signals and gain adjustment of each channel. The latter is based on the root mean square value (RMS) value of the signal and channel noise level. MRC is considered an optimal combiner for independent channels affected by Additive White Gaussian Noise (AWGN). This technique involves the weighing of signals from all branches, based on their signal-to-noise ratio (SNR), aligning the individual signals in phase, and then adding. It is a useful concept that is relevant to channel propagation, fading, and link budget considerations [2].

### *A. MRC receivers with Perfect and Imperfect CSI*

A communication-link channel property is referred to as channel state information (CSI). It describes the propagation of a signal from a transmitter to a receiver such that transmissions are adapted to current channel conditions. A reliable communication system with an increased data rate is achieved [2]. Time-division duplex (TDD) is mostly preferred as it provides CSI to a base station via uplink training [4,7]. In frequency division duplexing, CSI is critical. The reciprocity in the angular domain between the channels (uplink and downlink) is exploited and the support of the downlink channel is diagnosed from the other one [7].

### *B. Why Use MRC Receivers?*

1. Less fading- Signals in a multipath propagation environment are less likely to interfere with the MRC combination. Thus, signal quality is improved.

2. Improved reliability due to high gain in diversity-ensuring signals are correctly received such that the probability of errors becomes near zero.

3. Easy to Implement- Not computationally complex as compared to other receivers with advanced technologies. Thus, the requirement of less resources, expertise, and practicality in

real-life situations.

4. High coverage areas -suitable for communication in the long-range as the signals are properly detected, even in noisy environments.

5. MIMO systems adaptability- A huge number of antennas ensure that spectral efficiency is achieved.

### *C. Application of Deep Learning to Perfect and Imperfect CSI of MRC Receivers*

1. *Estimation of Channel:* The accuracy can be improved through deep neural training networks of received signal data sets, together with the respective CSI pairs. The deep learning models learn complex relationships, creating robust channel estimation, free from noise or incomplete channel information.

2. *MRC receivers signal detection:* deep neural network training such that received signal mapping can be done to respective transmitted symbols. Signal detection is thus accurately improved by the receiver, leading to enhanced system performance.

3. *Curbing Interference:* Interference patterns can be recognized and effectively suppressed or canceled. The receiver is thus able to extract the desired signal from a noisy and interference-prone environment.

4. *Hybrid CSI estimation techniques:* The network can have the ability to combine and leverage available information for accurate channel estimation. The limitations of Imperfect CSI can thus be overcome, along with improving MRC receiver performance.

5. *Network adaptation and optimization:* Parameter optimization of MRC receivers can be done based on the CSI information available. Based on the performance metrics and historical data information, optimal receiver parameters can be trained and configured for diverse channel conditions. Thus, improved receiver performance and resource utilization can be achieved.

### *D. Efficiency analysis*

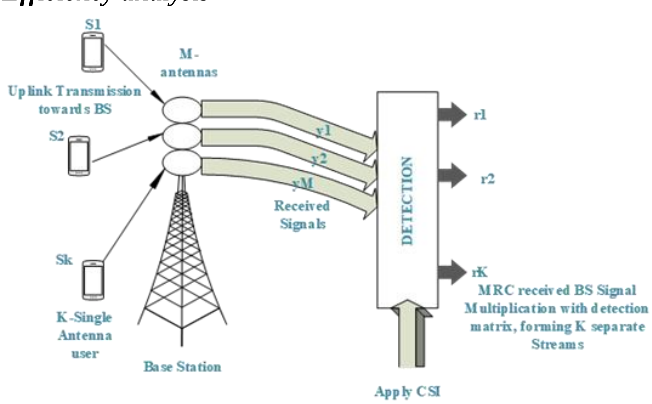



**Fig. 1**. MRC detection for uplink with Massive MIMO system

The following equations are given for Rayleigh fading channel for $M \geq 2$ and the lower bound for achievable uplink rate, is given by [7]. The parameters are described in below Table 1.

<u>*Perfect CSI*</u>

$$R_{P,k}{}^{mrc} = log_2\left(1 + \frac{p_u(T-1)\beta_k}{p_u \sum_{i=1,i\neq k}^{K} \beta_i + 1}\right) \quad (1)$$

<u>*Imperfect CSI*</u>

$$R_{IP,k}{}^{mrc} = log_2\left(1 + \frac{\tau p_u(T-1){\beta^2}_k}{(\tau p_u \beta_k + 1)\sum_{i=1,i\neq k}^{K} \beta_i + (\tau+1)\beta_k + \frac{1}{p_u}}\right) \quad (2)$$

**Spectral Efficiency** = $\sum_{k=1}^{K} R_{P,k}$ for perfect CSI and $\frac{C-\tau}{C}\sum_{k=1}^{K} R_{IP,k}$ for imperfect CSI.

**Table 1: Parameter Description**

| Parameter | Description |
|---|---|
| $P_u$ | Transmit Power per terminal |
| $T$ | Number of base station antennas per cell |
| $K$ | Number of users |
| $\beta_k$ | Fading channel coefficients of user $k$ |
| $\tau$ | Number of pilot symbols |
| $C$ | Coherence interval in symbols |

### *E. Error Performance analysis*

The Bit Error Rate for the MPSK signal in a Rayleigh fading channel is given as follows [8, 9]:

$$BER = \left(\frac{1}{log_2 M}\right)\left(p^T \sum_{i=0}^{T-1} \binom{T-1+i}{i} (1-p)^i\right) \quad (3)$$

Where $M$ is the Order of Modulation and $T$ is the Number of base station antennas. The Probability of bit error has been evaluated in [9] and given by equation (4).

$$P_b(E) = \frac{1}{2}\left(1 - \sqrt{\frac{\gamma_s}{T\eta_{MPSK} + \gamma_s}}\right) \quad (4)$$

where $\gamma_s$ refers to the SINR of the MRC receiver which can be found in (1) and (2).

$$\eta_{MPSK} = \frac{1}{2\, log_2 M sin^2\left(\frac{\pi}{M}\right)} \quad (5)$$

Moreover, the Bit Error Rate for the *MQAM* signal modulation in a Rayleigh fading channel is derived in [9] and given as

$$BER = \left(\frac{2}{log_2 M}\right)\left(\frac{\sqrt{M-1}}{\sqrt{M}}\right)\left(p^T \sum_{i=0}^{T-1}\binom{T-1+i}{i}(1-p)^i\right) \quad (6)$$

Where $M$, $T$ *and* $\gamma_s$ are the same as what was previously discussed. The Probability of error can be computed as

$$P_b(E) = \frac{1}{2}\left(1 - \sqrt{\frac{\gamma_s}{T\eta_{MQAM} + \gamma_s}}\right) \quad (7)$$

$$\eta_{MQAM} = \frac{2(M-1)}{3\, log_2 M} \quad (8)$$

## III. PROPOSED DESIGN AND METHODOLOGY

The Massive MIMO system was designed as per Fig. 1, with 200 antennas and different users (16 and 25). Moreover, it has importance in IoT applications, as it has the potential to revolutionize wireless communications. The design considerations pertaining to the choice of antennas, user configurations, and transmit power are explored. A massive number of devices are accommodated and the spectral efficiency is enhanced. The Rayleigh Fading channel can be theoretically incorporated as an input in the lab experiment, through coding. This requires random fading coefficient generation for dynamic channel effects. The transmitted signals are further modified using coefficients and the received signal is demodulated. The student tasks are analyzed in two ways. Firstly, a performance analysis, using the appropriate equations given above, is made pertaining to different user setups and channel conditions. This is achieved by using Rayleigh Fading Channel Simulation codes for data collection to compute SINR and BER. This aid in the enhancement of the student's understanding of the system's performance. Secondly, with different user and channel scenarios, spectral efficiency is explored as the data rates computed by the codes can be compared with the conventional MIMO. This helps to showcase the benefits of Massive MIMO under Rayleigh Fading conditions.

The list below illustrates the learning outcomes for the experimental setup

- Understanding the Massive MIMO principles with greater antenna and user numbers for wireless communication enhancement.
- Recognizing the random fading coefficient effects on signals.
- A brief overview of the signal processing techniques; how the signals are demodulated and analyzed.
- Gaining insights in BER and SINR performance metrics
- Comparing spectral efficiency for recognizing the merits inherent in Massive MIMO.
- Gaining practical experience in MATLAB® data analysis.
- Critical thinking and problem solving through results interpretation and deducing system performance.

Fig. 2 presents the development of algorithm to carry out various laboratory experiments which will be further detailed later in this work.

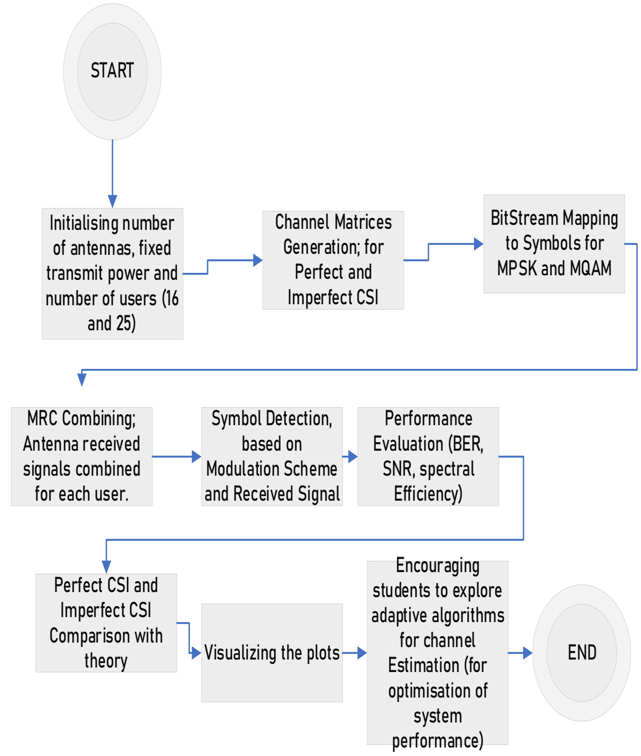



**Fig. 2. Algorithm development**

A cloud-based programming platform is one that harnesses cloud computing resources such that remote learning can be done. The simulations involve the execution of the codes. The students are also able to engage in diverse programming tasks. The integration of cloud technologies aims to educate future IT professionals wishing to enhance their knowledge in MATLAB. The programming tools, integrated within cloud frameworks allows for the development of methodologies that is used to enhance the research skills [10]. The cloud-based programming platform is introduced where the students can run the simulations remotely using MATLAB®. Fig. 3 illustrates the main steps in the implementation of MRC receivers employing MPSK (Perfect and Imperfect CSI), MQAM (Perfect and Imperfect CSI).

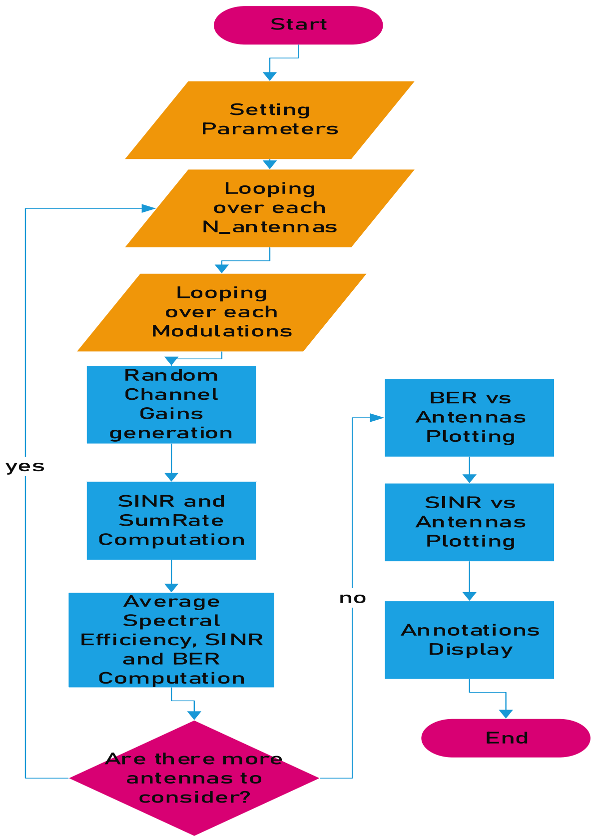



**Fig. 3. General flowchart for implementation of Laboratory experiments**

The details pertaining to the above are as follows:

- Initialization: The parameters were set and iterated over different antenna configurations and modulation.
- Signal Processing conducted: Channel gain simulation, SINR, "SumRate" computation, and BER evaluation were done such that extensive signal processing tasks could be conducted.
- A Decision point: It was decided if additional antennas were required for analysis.
- Conditional branching; if "Yes", the loop was iterated when there were more antennas to be considered. The process was then repeated for each configuration. While if "no", meaning that there were no additional antennas to be considered, a distinct analysis was executed. The BER or SINR against antennas were plotted with the annotations displayed.
- Termination: the experiment culminated where conclusions could be drawn.

## IV. IMPLEMENTATION

In what follows we describe fully the development of laboratory experiments for evaluating the efficiency and error performance of MRC receivers for Massive MIMO systems with various modulation schemes under exact and inexact channel estimates at the base station.

### *A. Experiment 1: MPSK modulation with Imperfect CSI*

*Learning Objectives:*

Signal quality metrics knowledge enhancement, data analysis and decision making, power parameter optimisation, data accumulation and averaging, experimental design along with mathematical concepts application. The flowchart that was used to evaluate the efficiency and error performance under Rayleigh fading and MPSK modulation with imperfect CSI is given in Fig. 4. The set of steps are executed as follows until a decision point is

reached. If the BER value ("PbFinal") is below an acceptable threshold that is not between 0 and 1, then the process is re-started. Else, the values are stored and plots observed. Fig. 5 shows extracts of MATLAB codes that were used to implement the flowchart of Fig. 4. Analytical models used are described by equations (2) to (5).

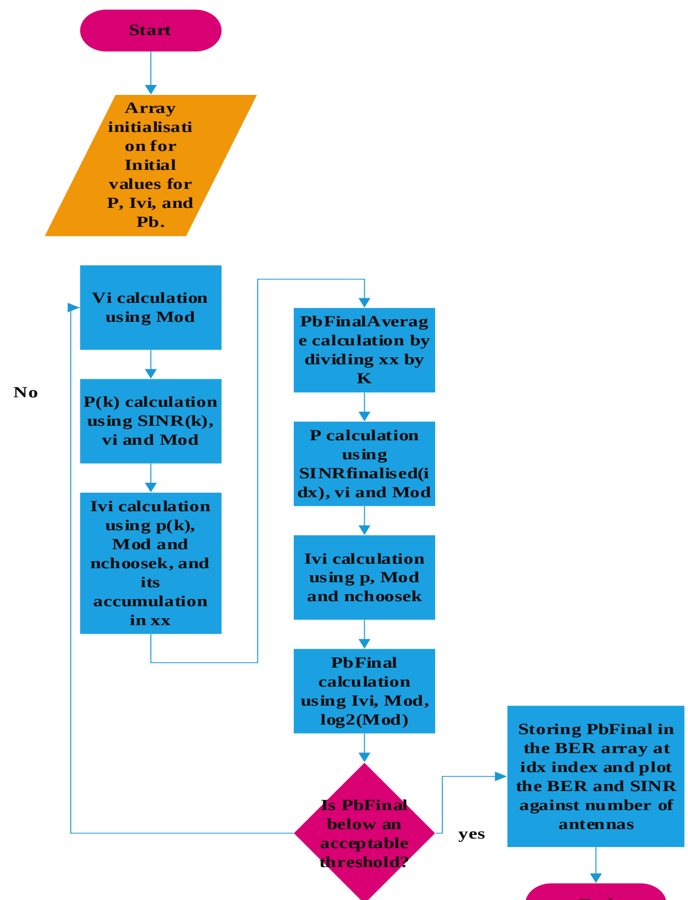



**Fig. 4. Flowchart for implementation of MRC receivers employing MPSK modulation with Imperfect CSI**

***Extract of MATLAB codes***

```
N_antennas = 20:20:200;% Number of antennas from 20 to 200 in steps of 20
BER = zeros(length(N_antennas),1);%BER
SNIRfinalised = zeros(length(N_antennas),1);%SINR
…………………………….
for idx =1:length(N_antennas)
   M=N_antennas(idx); % No of BS Antennas
   K=16; % No of Users
…………………………….
PudB=50;
Pu=db2pow(PudB);
%Coherence Time Interval is T=196
tau=14;  %Marzetta model
rmax=900;
rmin=150;
rincrement=(rmax-rmin)/(K);
   r=zeros(K,1);
   beta=zeros(K,1);
   shadowfadingstddeviation=6.31; % Shadow fading std deviation=8dB
……………………..
SEfinalised=0;
   SINRfinalised=0;
   realizations=10000; % Loop the simulation to calculate various massive MIMO system parameters
   for ii=1:realizations
……………………..
      for k=1:K
         r(k,1)=x+rincrement;
beta(k,1)=shadowfadingstddeviation/(power((r(k,1)/100),3.8));
         x=r(k,1);
      end
………………………….
SINRnumerator=zeros(K,1);
SINRdenominator=zeros(K,1);
SINR=zeros(K,1);
………………………….
for k=1:K
   y=0;
      x=0;
      SINRnumerator(k,1)=tau*Pu*(M-1)*randobeta(k,1)*randobeta(k,1);
      for i=1:K
         if(i~=k)
            y=x+randobeta(k,1); % can use beta array or randobeta
         end
         x=y;
   end
SINRdenominator(k,1)=(((tau*Pu*randobeta(k,1)+1)*y)+((tau+1)*randobeta(k,1))+ 1/Pu);
 end
……………………………….
SumRate=zeros(K,1);
      for k=1:K
            SINR(k,1)= SINRnumerator(k,1)./SINRdenominator(k,1);
            SumRate(k,1)= log2(1 + (SINR(k,1))); %Achievable SumRate
      end
…………………………………
      %SPECTRAL EFFICIENCY
      xx=0;
      yy=0;
      for k=1:K
         xx = xx+SumRate(k,1);
         yy=yy+SINR(k,1);
      end
      SEfinal=xx;
      SINRfinal=yy/K;
SINRfinalised=SINRfinalised/realizations;
   SNIRfinalised(idx) = SINRfinalised;
%CALCULATION OF ERROR RATES BY AVERAGING SINR OF ALL USERS
   vi= (1*log2(Mod)*sin(pi/Mod)*sin(pi/Mod))^(-1);
   p=0.5*(1-sqrt((SNIRfinalised(idx)/(M*vi+SNIRfinalised(idx)))));
    syms j integer
   Ivi=power(p,M)*(symsum((nchoosek(M-1+j,j))*(1-p)^j,j,0,M-1));
   PbFInal= (1/log2(Mod))*double(Ivi)
   BER(idx) = PbFInal;
```

**Fig. 5. Extract of MATLAB codes for Imperfect CSI and MPSK modulation**

***B. Experiment 2: MPSK modulation with Perfect CSI***

*Learning Objectives:*

Resource optimisation skills, trade-off considerations, iterative problem-solving along with dynamic system adaptation.

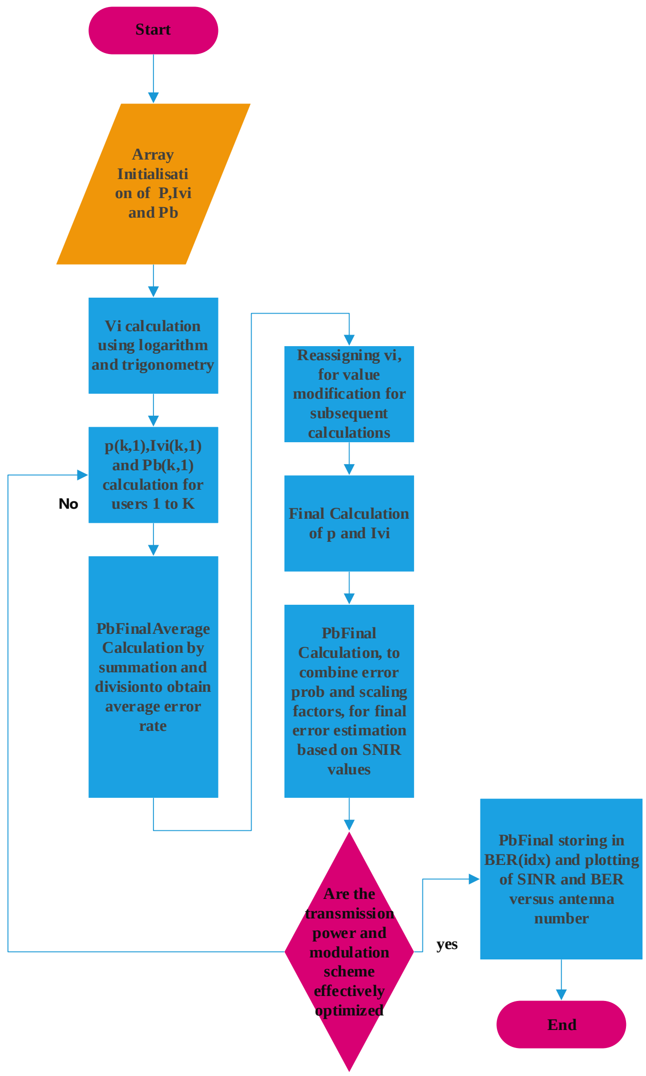



**Fig. 6. Flowchart for implementation of MRC receivers employing MPSK Perfect CSI**

The flowchart of Fig. 6 shows an experimental setup for MPSK perfect CSI. After a set of steps are executed, the decision point checks whether proper resources have been allocated for optimisation. If not, the relevant values are recalculated before plotting the results. Given in Fig. 7 are the extracts of MATLAB codes that can be used to implement Fig. 6. Equations (1) and (3-5) have been used in this experiment.

***Extract of MATLAB codes***

```
N_antennas = 20:20:200;% Number of antennas from 20 to 200 in steps of 20
BER = zeros(length(N_antennas),1);%BER
SNIRfinalised = zeros(length(N_antennas),1);%SINR
………………………………….
for idx =1:length(N_antennas)
   M=N_antennas(idx); % No of BS Antennas
   K=16; % No of Users
…………………………………..
PudB=50;
Pu=db2pow(PudB);
%Coherence Time Interval is T=196
tau=14;  %Marzetta model
rmax=900;
rmin=150;
rincrement=(rmax-rmin)/(K);
   r=zeros(K,1);
   beta=zeros(K,1);
   shadowfadingstddeviation=6.31;  % Shadow fading std deviation=8dB
………………………..
SEfinalised=0;
   SINRfinalised=0;
   realizations=10000;  % Loop the simulation to calculate various massive MIMO system parameters
   for ii=1:realizations
………………………..
      for k=1:K
         r(k,1)=x+rincrement;
beta(k,1)=shadowfadingstddeviation/(power((r(k,1)/100),3.8);
         x=r(k,1);
      end
…………………………….
SINRnumerator=zeros(K,1);
SINRdenominator=zeros(K,1);
SINR=zeros(K,1);
…………………………….
for k=1:K
   y=0;
      x=0;
      SINRnumerator(k,1)=Pu*(M-1)*randobeta(k,1); % can use beta array or randobeta
      for i=1:K
         if(i~=k)
            y=x+randobeta(k,1);  % can use beta array or randobeta
         end
         x=y;

      end
      SINRdenominator(k,1)=Pu*y + 1;


end…………………………………….
SumRate=zeros(K,1);
      for k=1:K
```

```
            SINR(k,1)=
SINRnumerator(k,1)./SINRdenominator(k,1);
            SumRate(k,1)= log2(1 + (SINR(k,1))); %Achievable
SumRate
      end
…………………………………….
      %SPECTRAL EFFICIENCY
      xx=0;
      yy=0;
      for k=1:K
         xx = xx+SumRate(k,1);
         yy=yy+SINR(k,1);
      end
      SEfinal=xx;
      SINRfinal=yy/K;
SINRfinalised=SINRfinalised/realizations;
   SNIRfinalised(idx) = SINRfinalised;
%CALCULATION OF ERROR RATES BY AVERAGING SINR OF
ALL USERS
   vi= (1*log2(Mod)*sin(pi/Mod)*sin(pi/Mod))^(-1);
   p=0.5*(1-
sqrt((SNIRfinalised(idx)/(M*vi+SNIRfinalised(idx)))));
    syms j integer
   Ivi= power(p,M)*(symsum((nchoosek(M-1+j,j))*(1-p)^j,j,0,M-
1));
   PbFInal= (1/log2(Mod))*double(Ivi)
   BER(idx) = PbFInal;
```

**Fig. 7. Extract of MATLAB codes to implement Perfect CSI and MPSK modulation**

### *C. Experiment 3: MQAM modulation with Perfect CSI*

*Learning Objectives:*

Applying MQAM calculations for signal processing, recognizing CSI, assessing system performance metrics, implementing MQAM and CSI in a code practically, applying theory to real-world situations, enhancing critical thinking to develop an optimized system.

The flowchart used in this experiment is given in Fig.8 and equations (1), (6-8) have been used. At the decision point of Fig. 8 the implemented system performance was assessed, ensuring that the satisfied criteria were met. If the criteria were not met; like unexpected BER or SINR values, then the whole process needed to be repeated. Else, the plots could be observed with no further modifications. We provide in Fig. 9 extracts of MATLAB codes to implement Fig. 8.

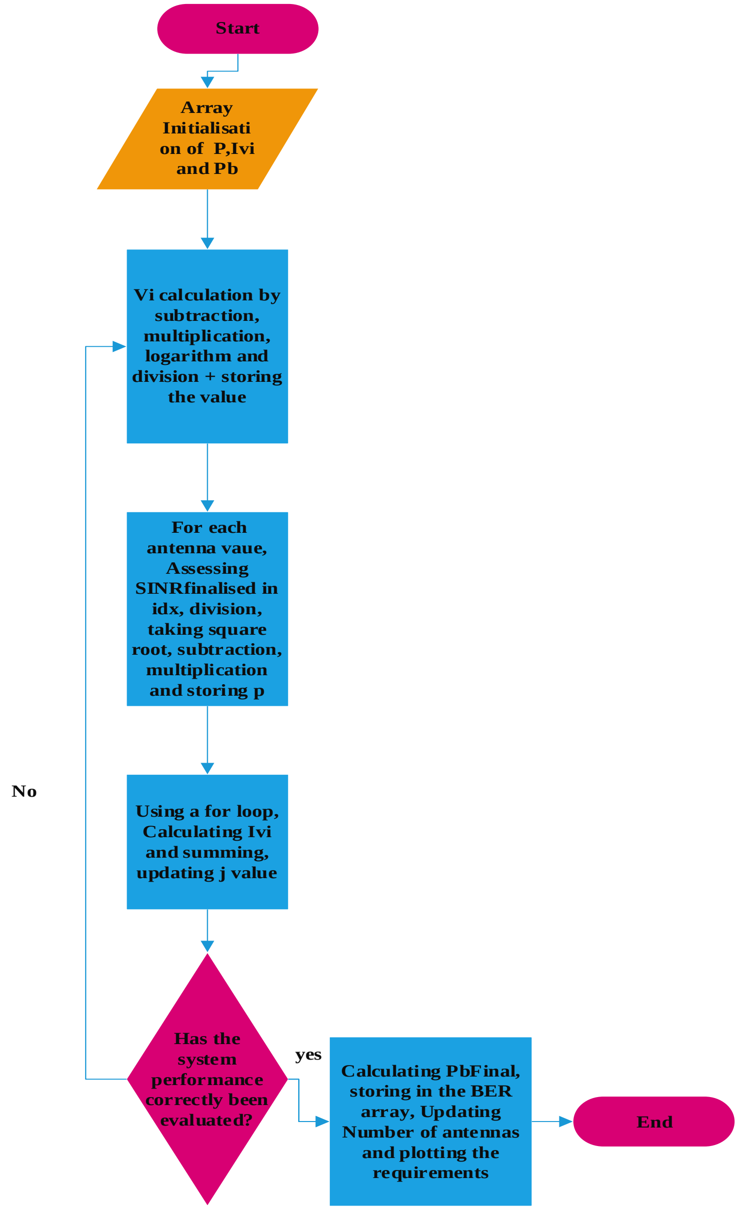



**Fig. 8. Flowchart in the implementation of MRC receivers employing MQAM Perfect CSI**

***Extract of MATLAB codes***

```
N_antennas = 20:20:200;% Number of antennas from 20 to 200
in steps of 20
BER = zeros(length(N_antennas),1);%BER
SNIRfinalised = zeros(length(N_antennas),1);%SINR
…………………………………
for idx =1:length(N_antennas)
   M=N_antennas(idx); % No of BS Antennas
   K=16; % No of Users
…………………………………..
PudB=50;
```

```
Pu=db2pow(PudB);
%Coherence Time Interval is T=196
tau=14;  %Marzetta model
rmax=900;
rmin=150;
rincrement=(rmax-rmin)/(K);
   r=zeros(K,1);
   beta=zeros(K,1);
   shadowfadingstddeviation=6.31; % Shadow fading std deviation=8dB
……………………..
SEfinalised=0;
   SINRfinalised=0;
   realizations=10000; % Loop the simulation to calculate various massive MIMO system parameters
   for ii=1:realizations
……………………..
      for k=1:K
         r(k,1)=x+rincrement;
         beta(k,1) = shadowfadingstddeviation/(power((r(k,1)/100),3.8));
         x=r(k,1);
      end
………………………….
SINRnumerator=zeros(K,1);
SINRdenominator=zeros(K,1);
SINR=zeros(K,1);
………………………….
for k=1:K
   y=0;
      x=0;
      SINRnumerator(k,1)=Pu*(M-1)*randobeta(k,1); % can use beta array or randobeta
      for i=1:K
         if(i~=k)
            y=x+randobeta(k,1); % can use beta array or randobeta
         end
         x=y;

      end
      SINRdenominator(k,1)=Pu*y + 1;
end……………………………….
SumRate=zeros(K,1);
      for k=1:K
            SINR(k,1)= SINRnumerator(k,1)./SINRdenominator(k,1);
            SumRate(k,1)= log2(1 + (SINR(k,1))); %Achievale SumRate
      end
…………………………………….
      %SPECTRAL EFFICIENCY
      xx=0;
      yy=0;
      for k=1:K
         xx = xx+SumRate(k,1);
         yy=yy+SINR(k,1);
      end
      SEfinal=xx;
      SINRfinal=yy/K;
SINRfinalised=SINRfinalised/realizations;
   SNIRfinalised(idx) = SINRfinalised;
%CALCULATION OF ERROR RATES BY AVERAGING SINR OF ALL USERS
    vi=(2*(Mod -1))/(3*log2(Mod)); %M-QAM
     p=0.5*(1-sqrt((SNIRfinalised(idx)/(M*vi+SNIRfinalised(idx)))));
   syms j integer
     Ivi= power(p,M)*(symsum((nchoosek(M-1+j,j))*(1-p)^j,j,0,M-1));
      PbFInal= 2/(log2(Mod))*(((Mod^0.5)-1)/(Mod^0.5))*double(Ivi);
         BER(idx) = PbFInal;
```

**Fig. 9. Extract of MATLAB Codes to implement MQAM modulation with perfect CSI**

***D. Experiment 4: MQAM modulation with Imperfect CSI***

*Learning Objectives:*

MQAM Imperfect CSI knowledge enhancement, MATLAB simulation proficiency along with iterative optimisation skills, parameter tuning, effective resource utilization besides real application scenarios for performance assessment.

The flowchart used in this experiment is given in Fig. 10 and equations (2), (6-8) have been used. At the decision point of Fig. 10 the implemented system performance was assessed, ensuring that the satisfied criteria were met. If the criteria were not met; like unexpected BER or SINR values, then the whole process needed to be repeated. Else, the plots could be observed with no further modifications. We provide in Fig. 11 extracts of MATLAB codes to implement Fig. 10.

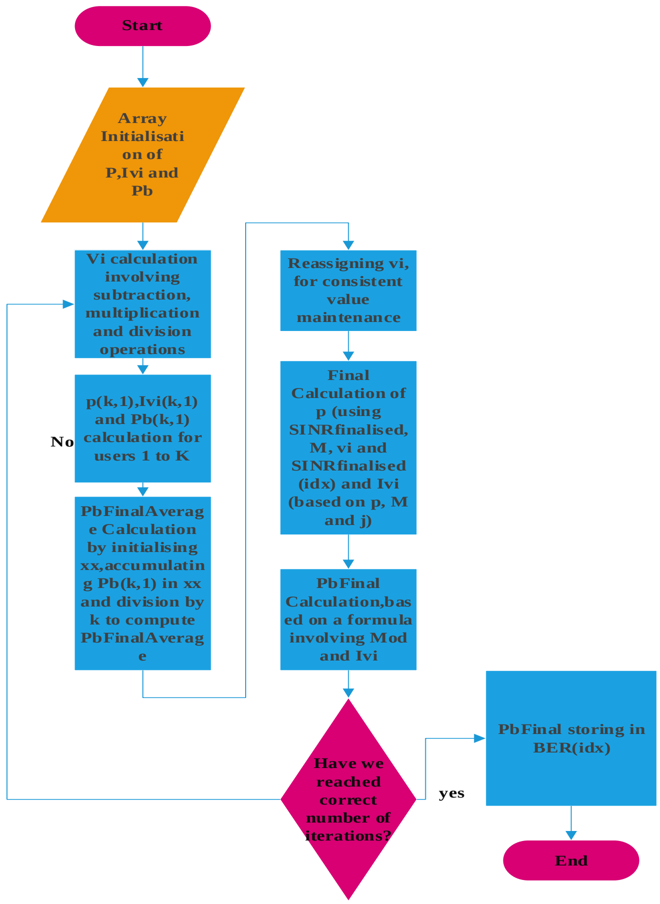



**Fig. 10. Flowchart in the implementation of MRC receivers employing MQAM Imperfect CSI**

***Extract of MATLAB codes***

```
N_antennas = 20:20:200;% Number of antennas from 20 to 200 in steps of 20
BER = zeros(length(N_antennas),1);%BER
SNIRfinalised = zeros(length(N_antennas),1);%SINR
…………………………….
for idx =1:length(N_antennas)
   M=N_antennas(idx); % No of BS Antennas
   K=16; % No of Users
……………………………..
PudB=50;
Pu=db2pow(PudB);
%Coherence Time Interval is T=196
tau=14;  %Marzetta model
rmax=900;
rmin=150;
rincrement=(rmax-rmin)/(K);
   r=zeros(K,1);
   beta=zeros(K,1);
   shadowfadingstddeviation=6.31; % Shadow fading std deviation=8dB
……………………..
SEfinalised=0;
   SINRfinalised=0;
   realizations=10000; % Loop the simulation to calculate various massive MIMO system parameters
   for ii=1:realizations
……………………..
       for k=1:K
          r(k,1)=x+rincrement;
          beta(k,1) = shadowfadingstddeviation/(power((r(k,1)/100),3.8));
          x=r(k,1);
       end
…………………………..
SINRnumerator=zeros(K,1);
SINRdenominator=zeros(K,1);
SINR=zeros(K,1);
…………………………..
for k=1:K
   y=0;
       x=0;
       SINRnumerator(k,1)=tau*Pu*(M-1)*randobeta(k,1)*randobeta(k,1);
       for i=1:K
          if(i~=k)
             y=x+randobeta(k,1); % can use beta array or randobeta
          end
          x=y;
      end

SINRdenominator(k,1)=(((tau*Pu*randobeta(k,1)+1)*y)+((tau+1)*randobeta(k,1))+ 1/Pu);
 end
………………………………….
SumRate=zeros(K,1);
       for k=1:K
             SINR(k,1)= SINRnumerator(k,1)./SINRdenominator(k,1);
             SumRate(k,1)= log2(1 + (SINR(k,1))); %Achievable SumRate
       end
……………………………………..
       %SPECTRAL EFFICIENCY
       xx=0;
       yy=0;
       for k=1:K
          xx = xx+SumRate(k,1);
          yy=yy+SINR(k,1);
       end
```

```
    SEfinal=xx;
    SINRfinal=yy/K;
SINRfinalised=SINRfinalised/realizations;
  SNIRfinalised(idx) = SINRfinalised;
vi=(2*(Mod -1))/(3*log2(Mod)); %M-QAM
  p=0.5*(1-sqrt((SINRfinalised/(M*vi+SINRfinalised))));
  syms j integer
  Ivi=  power(p,M)*(symsum((nchoosek(M-1+j,j))*(1-p)^j,j,0,M-1));
  PbFInal=  2/(log2(Mod))*(((Mod^0.5)-1)/(Mod^0.5))*double(Ivi)
  BER(idx) = PbFInal;
```

**Fig. 11. Extract of MATLAB codes for MQAM modulation with imperfect CSI**

## V. OUTPUT SIMULATION RESULTS OF LABORATORY EXPERIMENTS

In this section, the output results obtained from several experiments are described. Data extraction was performed for the following three parameters:

1. SINR: the received signal vector was used to compute the SNR, such that the signal quality could be assessed relative to the noise level.
2. BER: the received and transmitted symbols were compared to determine if the data was accurately transmitted.
3. Spectral Efficiency: the system bandwidth along with the number of bits transmitted per channel used helped determine how the system efficiently utilized the available bandwidth.

Thus, the students are able to extract performance metrics from the received signal. Valuable insights are gained into the performance of Massive MIMO under perfect and imperfect CSI, when user number is varied and how the algorithm used has an impact on the performance of the system. The data collected during the Massive MIMO simulations will be processed and their key performance analyzed. The metrics concerned are SNR, BER and Spectral Efficiency. The visualizations will then be created, which includes plots and graphs for results representation. The behaviour of Massive MIMO can thus be analyzed under diverse conditions, comparing parameter performances.

For the case of Perfect CSI, massive MIMO simulation will be performed assuming perfect Channel State Information. Thus, error-free knowledge channel conditions and accurate information of all antennas and user are possessed by the receiver. Thus, the students are able to analyze the different performance metrics when MRC receivers operate optimally, with accurate CSI. For the case of imperfect CSI, massive MIMO will be simulated under imperfect CSI conditions such that the students could study how the performance metrics are affected by channel estimation errors. They can thus understand the challenges posed by such a system and how the Massive MIMO performance system can be degraded. The following plots were obtained by collecting data from the experiments described earlier.

### *A. Error performance curves for MPSK modulation and Perfect/Imperfect CSI*

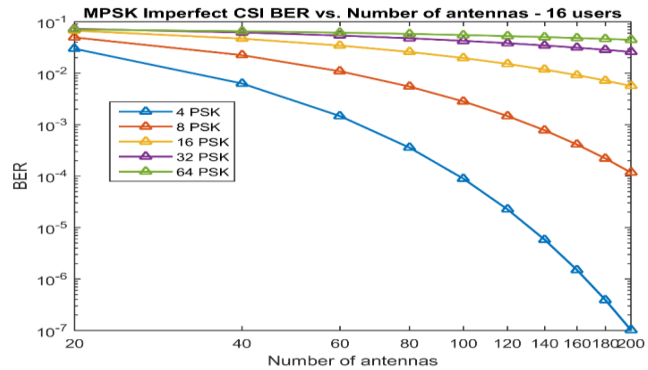



**Fig. 12. Error performance curves for Imperfect CSI, K=16.**

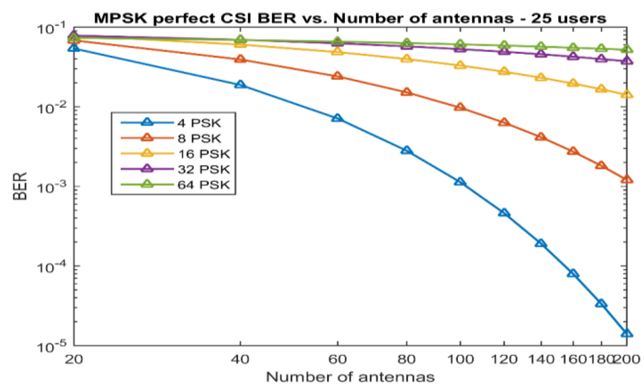



**Fig. 13. Error performance curves for Perfect CSI, K=16.**

### *B. Error performance curves for MQAM modulation with Perfect/Imperfect CSI*

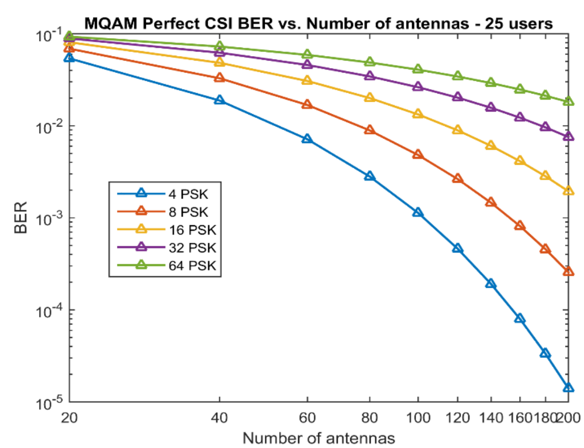
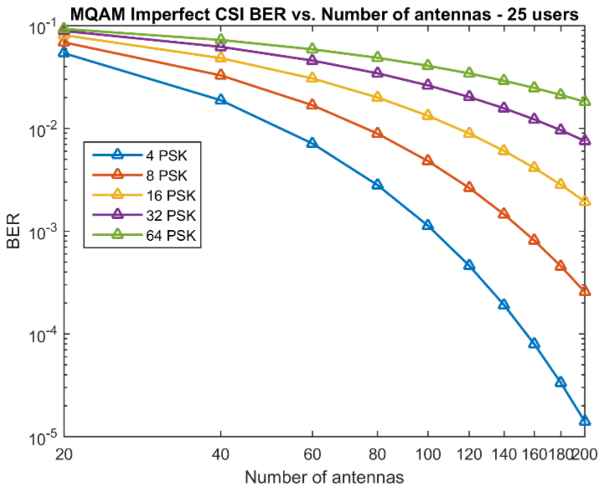



**Fig. 14. Error performance curves for Perfect CSI, K=25.**




Re

**Fig. 15. Error performance curves for Imperfect CSI, K=25.**

### *C. Spectral Efficiency curves*

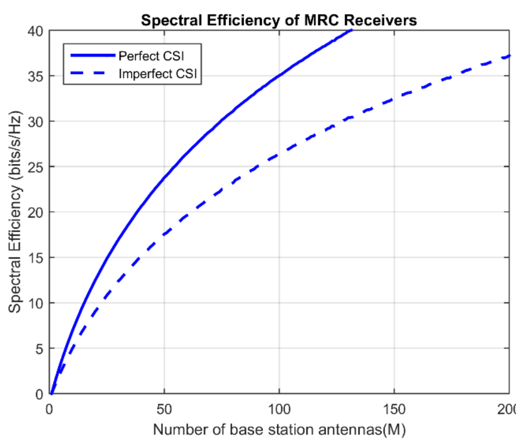



**Fig. 16. Spectral efficiency curves for 16 Users, 10dB Transmit Power**

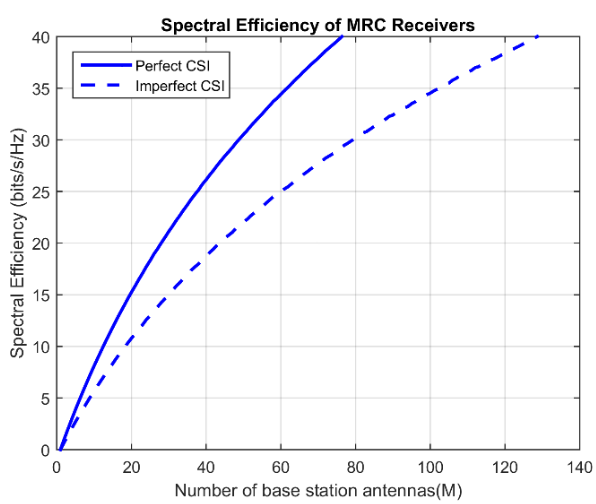



**Fig. 17. Spectral efficiency curves for 25 Users, 10dB Transmit Power.**

### *D. Results discussions and Future works*

- It can be seen that for all the cases, MPSK or MQAM, with perfect or imperfect CSI, as the number of antennas increases, the BER decreases in a concave down manner. Upon the addition of more antennas, the received signal spatial diversity can be exploited such that fading characteristics are exhibited. This is because of an antenna's specific position and its location in an environment. When signals from multiple antennas are combined, negative effects due to fading are mitigated by the MRC receiver resulting in a **reduced Bit Error Rate**. Hence, correct interpretation of transmitted symbols can be made by the receiver and interference and noise are suppressed. The spatial signatures of desired and interfering signals are taken into consideration and the signals are optimally aligned and combined. In this way, the SINR increases. This improves the signal quality as compared to noise leading to correct symbol detection.
- For massive MIMO systems, we consider the number of antennas range to be greater than the number of users. Thus, a very good representation of the BER plot is obtained. The transmitted signals are better captured and received. The excess antennas are used to gather more signal energy such that noise impact is minimized. The SINR increases leading to a reduction in the BER.
- With regards to the analysis of spectral efficiency for massive MIMO system experiments and simulation curves show that with K=16, at a value of 10 dB for $P_u$, coherence interval of T=196, it can be seen that for a given value of the number of base station antennas, the spectral efficiency for an imperfect CSI is lower than that for the case of perfect CSI for an MRC receiver. For instance, at M= 100, a Spectral efficiency of around 25 bits/s/Hz for an imperfect CSI is achieved while for the same M, the efficiency for a perfect CSI is approximately 35 bits/s/Hz.

Future endeavors contributing to the perpetual Massive MIMO system advancement and optimization have to be devised. For instance, there can be an investigation of diverse fading models such as those based on machine learning. The latter encourages data-driven, deep, and reinforcement learning, along with several approaches. These allow the learning of complex mapping between channel parameters and real-world fading characteristics accordingly. Moreover, the project could consider adding advanced receiver techniques. These include equalization algorithms, successive interference cancellation, and more adaptive modulation techniques besides MPSK and MQAM. Moreover, implementing the work in real-life, field trials, and practical deployment can be done for validating the system's performance. In this way, Massive MIMO systems can be optimized to achieve an enhanced wireless communication system. Also, the whole project can be implemented using a Rician fading model.

## VI. CONCLUSION

With the introduction of accreditation of the existing undergraduate engineering programmes at the University of Mauritius, the lack of laboratory resources is a challenge for emerging areas of technology in the industry. The work presented in this paper has analyzed the implementation of laboratory experiments to address this challenge. During classroom teaching, the instructor described the foundations of massive MIMO systems for 5G cellular networks from a signal processing perspective. The students are organized in groups and tasked to develop laboratory experiments which are described in this paper. It can be deduced that the potential of Massive MIMO systems has been explored along with MRC receivers. With the use of perfect and imperfect Channel State Information, valuable insights have been gained. These include technological performance in real-world applications. With a given number of antennas and a number of users, the Bit Error Rate can be evaluated with regard to MPSK and MQAM modulation techniques. The SINR can also be achieved to better understand the performance of the system when various modulation schemes, antenna numbers, and user numbers are considered. This has aided in determining the behavior and trade-offs of the systems. This project is feasible as there are no additional costs required in terms of hardware and does not cause any adverse effects on the environment of the University.

## REFERENCES


1. Lin, X., & Lee, N. (Eds.) 5G and Beyond. Springer International Publishing. https://doi.org/10.1007/978-3-030-58197-8, 2021.
2. Björnson, E., Hoydis, J., & Sanguinetti, L. Massive MIMO Networks: Spectral, Energy, and Hardware Efficiency. *Foundations and Trends® in Signal Processing*, *11*(3-4), 154–655, 2017. https://doi.org/10.1561/2000000093
3. Ngo, H. Q., & Larsson, E. G. No Downlink Pilots Are Needed in TDD Massive MIMO. *IEEE Transactions on Wireless Communications*, *16*(5), 2921–2935, 2017. https://doi.org/10.1109/twc.2017.2672540
4. Hien Quoc Ngo, Larsson, E. G., & Marzetta, T. L. Energy and Spectral Efficiency of Very Large Multiuser MIMO Systems. *IEEE Transactions on Communications*, *61*(4), 1436–1449, 2013. https://doi.org/10.1109/tcomm.2013.020413.110848
5. Lu, W., Wang, Y., Fang, Q., & Peng, S. Downlink compressive channel estimation with support diagnosis in FDD massive MIMO. *EURASIP Journal on Wireless Communications and Networking*, *2018*(1). https://doi.org/10.1186/s13638-018-1131-4
6. F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, ''Scaling up MIMO: Opportunities and challenges with very large arrays,'' *IEEE Signal Process. Mag.*, vol. 30, no. 1, pp. 40–60, Jan. 2013.
7. Marzetta, T. L., Larsson, E. G., Yang, H., & Ngo, H. Q. Fundamentals of Massive MIMO. In *Cambridge University Press*. Cambridge University Press, 2016. https://www.cambridge.org/core/books/fundamentals-of-massive-mimo/C43AF993A6DA7075EC5F186F6BAC914B
8. Kamal, M. A., Raza, H. W., Alam, M. M., Su'ud, M. M., & Sajak, A. binti A. B. Resource Allocation Schemes for 5G Network: A Systematic Review. *Sensors*, *21*(19), 6588,2021. https://doi.org/10.3390/s21196588
9. ALTAMIRANO, C. D., MINANGO, J., MORA, H. C., & ALMEIDA, C. D. *BER Evaluation of Linear Detectors in Massive MIMO Systems Under Imperfect Channel Estimation Effects* [Review of *BER Evaluation of Linear Detectors in Massive MIMO Systems Under Imperfect Channel Estimation Effects*]. IEEE; IEEEAccess, 2019. https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8917985
10. Caban, S., Lerch, M., Pratschner, S., Zöchmann, E., Svoboda, P., & Rupp, M. Design of Experiments to Compare Base Station Antenna Configurations. *IEEE Transactions on Instrumentation and Measurement*, *68*(10), 3484–3493, 2019. https://doi.org/10.1109/tim.2018.2880941